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In-process tool condition monitoring systems in CNC turning operations

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In-process tool condition monitoring systems in CNC turning operations

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ABSTRACT

The present study shows the development of in-process tool condition monitoring systems utilizing signal decomposition technique, statistical data analysis, and artificial neural networks system. Two systems; (1) the system based on the multiple regression, (2) the system based on artificial neural networks with back-propagation learning algorithms were developed.

The raw signals obtained from two sensors (tri-axial accelerometer and AE sensor) with different machining parameters and tool conditions were examined and decomposed into six components by utilizing a wavelet transformation. The most significant components of each signal were found by statistical method and implemented to develop two in-process tool monitoring systems.

Before the multiple regression system was developed, a statistical process was performed to eliminate the effects of machining parameters from the signals of the accelerometer and AE sensor. The prediction performance improved 12.6% from the process.

In order to maximize the benefit of artificial neural networks system in tool monitoring systems, a novel approach was performed in this study. A great number of networks structures were tested systemically to find an optimized structure for the artificial networks tool condition monitoring system. The technique provided benefits of not only saving time but also testing all possible structures more accurately compared with the traditional manual trial-and-error methodology.

The developed statistical multiple regression tool condition monitoring system showed 90% accuracy, and the developed artificial neural networks tool condition monitoring system showed 97% accuracy from 151 tests with the reject flank wear size of 0.00787 inch (0.2 mm) or larger.

The successful development of the tool condition monitoring systems can provide a practical tool to reduce downtime related with tool changes and minimize the amount of scrap in metal cutting industry. Implications of the study and recommendations for further research were provided.

CHAPTER 1. INTRODUCTION

The metal cutting process has played an important role in modern manufacturing history. In addition to being a primary manufacturing process, metal cutting is also a finishing operation used to achieve very high dimensional accuracy and close to a desired surface finish (Singh, 1996). The most common metal cutting processes are milling, drilling, turning, and grinding.

These metal cutting processes relied on highly skilled labor until the mid-1950s, when automated machining began to replace human operators with more efficient, less costly automated machining processes. In a short time, automated machining captured a great deal of attention from the major manufacturers, who were seeking to reduce production costs and increase product quality. Manufacturers saw that automated metal cutting processes could replace traditional labor, decrease production costs, increase productivity, and enhance product quality (O'Donnell, Young, Kelly, & Byrne, 2001; Park & Kim, 1998; Purushothaman & Srinivasa, 1994). As a result, automated metal cutting processes soon replaced highly skilled labor in many traditional machine shops.

Meanwhile, the industry also demanded another task of manufacturers. Customers' product demands became more individualistic, products became more varied, and the complexity of manufacturing processes increased. Manufacturers needed new technologies and methods that would allow small-batch production to gain the economic advantages of mass production (Raj et al., 2000; Singh, 1996; Willow, 2002). The development of CIM (Computer-Integrated Manufacturing) and FMS (Flexible Manufacturing Systems) seemed to be ideal solutions for many of these problems. The combination of CIM and FMS technology showed promise for increasing machining flexibility (the capability to perform a variety of operations on a variety of part types) in addition to flexibility in routing, process, product, production, and expansion (Singh, 1996).

Although the combination of CIM and FMS technologies showed great promise as a cost-effective solution to meet new demands, CIM-FMS systems could not be implemented until certain prerequisites were met. One major prerequisite was uninterrupted machining. Manufacturing processes must be uninterrupted to achieve maximum efficiency (Venkatesh, Zhou, & Caudill, 1997). However, deteriorating process conditions often force manufacturers to interrupt machining processes to respond to deteriorating production conditions such as tool wear. Thus, developing an effective means of monitoring machine conditions has become one of the most important issues in the automation of the metal cutting process (Li, Dong, & Venuvinod, 2000).

Among the many possible machining conditions that could be monitored, tool wear is the most critical for ensuring uninterrupted machining. Any effective monitoring system must sense tool conditions, allow for effective tool change strategies when tools deteriorate, and maintain proper cutting conditions throughout the process (Lee, Kim, & Lee, 1998). If the monitoring function cannot maintain proper cutting conditions, the cutting process could result in poor surface quality, dimensional workpiece defects, and even machine defects (Li et al., 2000).

Researchers have sought reliable methods to monitor tool wear. These methods are an area of active research because tool condition strongly influences the surface finish and dimensional integrity of the workpiece, as well as vibration in the tool. Furthermore, a reliable tool wear monitoring system can reduce machine downtime caused by changing the tool, thus leading to fewer process interruptions and higher efficiency. The information obtained from the tool wear sensors can be used for several purposes, including the establishment of tool change policy, economic optimization of the machining operation, on-line process manipulation to compensate for tool wear, and, to some extent, the avoidance of catastrophic tool failure.

The traditional process for predicting the life of a machine tool involves Taylor's (1906) equation for estimating tool life: $VT^n = C$, where V is cutting speed, T is tool life, and n and C are coefficients. This equation has played an important role in machine tool development (Kattan & Currie, 1996).

Since advanced machining was introduced in the mid-1900s, various methods to monitor tool wear have been proposed, expanding the scope and complexity of Taylor's equation. However, none of these extensions has been applied universally, due to the complex nature of the machining process (Xiaoli & Zhejun, 1998).

More automated approaches were attempted using computer-numerical control (CNC) technology. However, the CNC approach also has several obstacles to widespread implementation, including:

- Narrow learning capability of CNC machines
- Limited flexibility of the CNC controller
- Relatively large dynamic errors encountered in CNC operations
- Sensor noises
- Variability between machines (Chen, 2000)

Many studies tried to overcome these limitations by finding and utilizing proper sensor technologies and signal process techniques. Therefore, numerous sensor techniques were introduced and tested in tool wear monitoring studies.

Tool condition monitoring methods can be classified into direct and indirect methods, depending on the source of signals collected by sensors. Direct methods sense tool conditions by direct measurement of the tool. Direct methods include optical, radioactive, and electrical resistance. Alternatively, indirect methods sense the tool condition by measuring secondary effects of the cutting process, such as acoustic emission (AE), sound vibrations, spindle and feed motor current, cutting force, and machining vibration. Direct methods are beneficial because they take close readings directly from the tool itself. By contrast, indirect methods must rely on conditions other than the tool itself to judge tool condition. However, direct methods are limiting because the machining process must be interrupted to make the direct measurements (Bradley & Wong, 2001; Karthik et al., 1997; Kassim, Mannan, & Jing, 2000). As a result, machine downtime increases, as do costs for tool condition monitoring. Researchers therefore have preferred indirect methods to study in-process tool condition monitoring systems.

Since indirect methods do not require access to the tool itself to measure the tool conditions, signals that indicate the tool condition can be gathered in real time, while the machine is running. However, despite the benefits of in-process measurement, indirect methods also have some disadvantages. Since the information (or signals) collected by indirect sensors does not contain direct measurements of the tool conditions, other systems are required to correlate the indirect measurements with tool condition. Additionally, indirect measurements are weakened by noise factors associated with the machining process. Noise factors tend to weaken or totally eliminate relationships between the indirect information (or signals) and actual tool conditions. For indirect, in-process measurement to be effective, methods that can identify significant signal components and eliminate the interfering noise are required.

Many studies have sought to correlate indirect measurements with actual tool conditions. The most popular methods for establishing this correlation were:

- statistical regression techniques (Bonifácio & Diniz, 1994; Choudhury & Kishore, 2000; Jennings & Drake, 1997; Jun & Suh, 1999; Lee, Kim, & Lee, 1998),
- fuzzy logic (Xiaoli & Zhejun, 1998; Ming, Xiaohong, & Shuzi, 1999),
- artificial neural networks (Chen & Jen, 2000; Choudhury, Jain, & Rao, 1999; Dimala Jr., Lister, & Leighton, 1998; Hong, Rahman, & Zhou, 1996; Özel & Nadgir, 2002; Purushothaman & Strinivasa, 1994), and
- fuzzy-neural networks (Balazinski et al., 2002; Chen, 2000; Chungchoo & Saini, 2002; Kuo, 2000).

In many of the aforementioned studies, the relationships between indirect signals and tool condition were weak because unknown factors and noise factors diluted the signals collected by the indirect sensors during machining.

Some studies attempted to eliminate or minimize noise factors from the information collected by indirect sensors. Wavelet transform methods were used to remove noise factors from the information collected by the sensors (Al-Habaibeh & Gindy, 2001; Tansel, Mekdeci, & Charles, 1995; Xiaoli & Zhejun, 1998). These studies showed that a wavelet transform process can increase the correlation between the de-noised signals and tool conditions (Wu &

Du, 1996). However, these studies still could not separate the significant component of the indirect signals that created the strong relationship with tool conditions.

A limited number of sensors have been adopted in most studies involving indirect sensing systems. The most widely used indirect sensor is the dynamometer, which has been used to measure the forces during the cutting processes (Chen, 2000; Ertune & Loparo, 2001; Lee, Kim, & Lee, 1998; Stein & Huh, 2002); however, applying the dynamometer is not practical because of its high cost and lack of overload protection (Li, 2001b).

The acoustic emission (AE) sensor is another sensing technology that has been used in a number of studies (Li, 2002; Liang & Dornfeld, 1989), but it is limited in its application by its noise integrity (Dimla Sr., 2000). Some studies adopted multi-sensor techniques to improve tool condition monitoring systems (Dimla Jr., Lister, & Leighton, 1998; Kuo, 2000; O'Donnell et al., 2001; Quan, Zhou, & Luo, 1998; Scheffer & Heyns, 2001; Silva, Reuben, Baker, & Wilcox, 1998). By combining multiple sensing technologies, these studies sought to develop more robust in-process tool condition monitoring systems.

Chapter 2 reviews the major sensor technologies and methods of analyzing tool wear.

Purpose of the Study

The purposes of this study are as follows:

- The main purpose of the study was to develop a tool condition monitoring (TCM) system that streamlines the machining process by reducing the number of process interruptions created by tool wear. This system utilizes indirect measurement of signals in a CNC turning operation machine.

- To isolate the significant components of the signals collected by the multi-sensors, this study utilized wavelet transform and decomposition techniques as signal processing tools.
- Using the significant components of the signals, an in-process tool monitoring system was developed using a statistical regression (SR) technique and an artificial neural networks (ANN) system.
- A multilayer neural network system with a back-propagation (BP) learning algorithm was implied in developing the ANN tool condition monitoring system.

Assumptions of the Study

This study made the following assumptions:

- The amount of tool wear and the signals detected by sensors during the cutting process have a significant relationship. Under the assumed relationship, the amount of flank wear of an insert tool will be predicted by the detected signals and machining parameters.
- Tool wear does not occur during the process of data acquisition in the cutting process. This assumption applies to the following two cases.
  - The amount of tool wear during a cutting process under a certain cutting condition is measured from the beginning of the cutting to the end.
  - The amount of tool wear of the tool tested under different cutting conditions is consistent.
- The noise factors are consistent during the acquisition of data. In other words, the amount of process noise and sampling noise are the same under the same cutting conditions, even though the amount of tool wear is different.

- The integration of the workpiece material and condition is consistent during a single cutting under one cutting condition, and among the cuttings under different cutting conditions. The differences in hardness of the experimental workpieces are assumed to be insignificant and thus can be ignored.

Impacts of the Study

The following impacts can be expected from the study.

- By utilizing the developed in-process tool condition monitoring system, manufacturers can expect a dramatic reduction of machine downtime related with tool changes in turning operations.
- The in-process tool condition monitoring system developed in this study also promises full utilization of the machining tool. Since manufacturers use a tool change policy based on their experience or the suggestions of manufacturers, most of the time they cannot fully utilize a cutting tool due to downtime while the policy is being enacted. This practice leads to the tool being changed more frequently than is necessary. The system proposed in the current study will alleviate this downtime.
- Since there is a direct correlation between the tool change times, machine downtimes, and higher numbers of tools, a cut in direct manufacturing costs can be expected as a result of implementing the system developed in this study.

CHAPTER 2. LITERATURE REVIEW

Several technologies and studies are involved in the study of tool condition monitoring systems (e.g., cutting mechanism in machining, tool wear mechanism, signal processing, intelligent decision-making systems, etc.). In this chapter, three main topics are discussed. First, the mechanism and properties of turning operations and tool wear are discussed in terms of insert tool identification and tool coating materials. Second, signal processing technologies will be introduced, including traditional methods (time-series analysis), Fourier transform, and Wavelet transform. Third, artificial neural networks and a learning algorithm will be discussed.

Turning Operation and Tool Wear

Along with milling, drilling, and grinding, turning operations are one of the major, conventional metal cutting processes used to produce cylindrical products. This section briefly introduces turning operations, cutting tools, and the tool wear mechanism in machining.

The turning machine and its products

Turning is a common and versatile machining process for producing cylindrical, conical, or irregularly shaped internal or external surfaces on a rotating workpiece (Singh, 1996). The lathe, in use since the Middle Ages (5th century to 15th century AD), is a common machine tool for turning operations. The modern lathe machine capable of mass-producing identical parts was developed in the early 1800s. These manual processes are contrasted with contemporary computer numerical control (CNC) turning machines. Typical parts produced by turning operations include pins, shaft, spindles, handles, and various other components having O-ring grooves, holes, threads, and many other shapes. Cutting operations that can be completed on a lathe include straight turning, taper turning, profiling, turning and external grooving, facing, face grooving, drilling, boring and internal grooving, cutting off, threading, and knurling. The various cutting parameters, such as spindle speed, feed rate, and depth of cut, impact machining time, tool life, surface production, dimensional accuracy, and cost of the part produced.

Machining parameters in the turning operation

The machining parameters that determine the rate of metal removal are cutting speed, feed rate, and depth of cut. The combination of machining parameters and the characteristics of the material to be cut determine the power required to make the cut. The machining parameters must be selected to stay within the power available on the machine tool to be used. Since there is a direct relationship between tool life and machining parameters (tool life is reduced when cutting speed is increased), the tool life also should be considered when determining the machining parameters. Figure 2.1 shows the machining parameters of the turning operation.

The first step in determining the machining parameters is to select the depth of cut for machining. Depth of cut is limited by the amount of metal that is to be machined from the workpiece, the power available on the machine tool, the rigidity of the workpiece and the cutting tool, and the rigidity of the setup. Depth of cut has the least effect upon the tool life, so the heaviest possible depth of cut always should be used. The second step is to select the feed speed for machining.

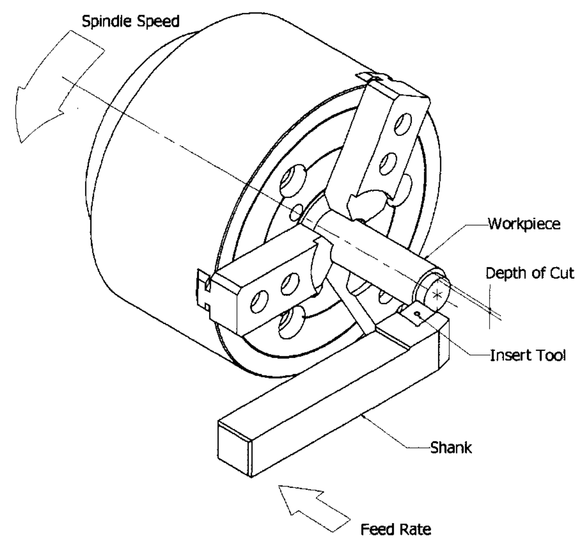


Figure 2.1. Schematic illustration of turning operation

The available power must be sufficient to make the required depth of cut at the selected feed rate. The maximum possible feed speed that will produce an acceptable surface finish should be selected. The third step is to select the cutting speed. Although many machining handbooks provide a recommended combination of cutting speeds and feeds for many materials, an experienced operator often will adjust the combination based on the workpiece and tool materials to obtain optimal surface characteristics and efficiency. However, in general, the depth of cut is selected first, followed by the feed, and, finally, the cutting speed (Oberg, Jones, & Ryffel, 2000).

Cutting tools for turning machines

It is well known that the efficiency of the cutting process varies depending on tool material and geometry. Since turning operations were introduced, the tool design and its material techniques have been greatly enhanced. This section briefly introduces the cutting tools of turning operations.

Insert tool and identification

A large proportion of modern cutting tools are indexable inserts and tool holders. Dimensional specifications of the inserts and tool holders are given in the American National Standard ANSI B212.12-1991. Several types of tools are used to create indexable inserts, including single-point cutting tools, which have a cutting edge at one end, most modern face milling cutters, side milling or slotting cutters, boring tools, and a wide variety of special tools (Oberg et al., 2000). The objective of this type of tooling is to provide an insert with several cutting edges. When an edge is worn, the insert is indexed in the tool holder until all the cutting edges have deteriorated, after which it is discarded. The insert is not intended to be reground since the inserts are often coated by hardened materials. The advantages are that the tool's cutting edges can be changed rapidly without removing the tool holder from the machine; tool-grinding costs are eliminated; and the cost of the insert is less than the cost of a similar, brazed carbide tool. Depending on the raw material and cutting process, the insert size and shape must be chosen carefully.

To select a tool size and shape, most insert tool manufacturers use either the American National Standards Institutes (ANSI) indexable insert identification system or the International Organization of Standards (ISO) systems to describe an insert in its entirety. The ANSI system is explained in this section.

The ANSI standard identification consists of up to ten positions. Each position defines a characteristic of the insert, as shown in Figure 2.2. Since the carbide insert was introduced, it has been accepted widely because of its hardness and rigidity. By applying coatings, more wear-resistant inserts were created, allowing much harder material production. Some examples of the coating insert and its properties are shown in the next section.

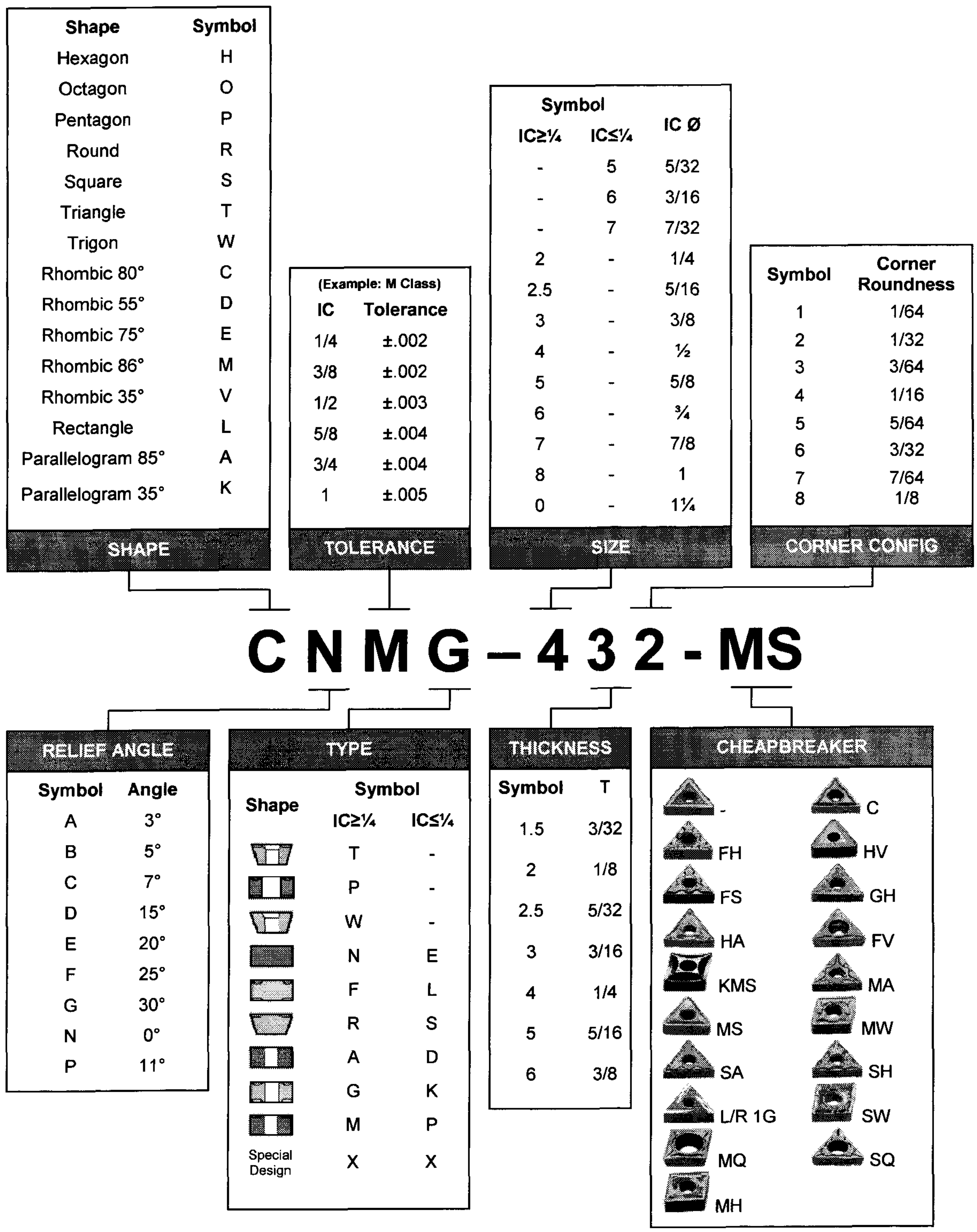


Figure 2.2. ANSI insert nomenclature (Mitsubishi Materials Co., n.d.; Thalmann, 1995)

Insert tool coating materials

Several coating materials have been developed to increase the durability, mechanical properties, and effectiveness of removing heat from the "hot spot" of the tool (Nedelik & Lux, 1999). The most frequently used coating layers are titanium carbide (TiC), aluminum oxide (Al_2O_3), and titanium nitrite (TiN) (Bonifácio & Diniz, 1994). TiC has a strong resistance to flank wear, TiN helps to increase the resistance to crater wear and decrease the coefficient of friction between tool and workpiece and between tool and chips, and Al_2O_3 contributes to the thermal and chemical stability of the tool (Shaw, 1984). At low cutting speeds, when abrasion is the main wear mechanism, the presence of a TiC coating will increase tool life greatly. However, flank wear does not depend on the thickness of the coating (Dearnley, 1985). As the cutting speed increases, diffusion becomes an important wear mechanism due to high temperatures. In these instances, the presence of a coating with thermal and chemical stability (such as Al_2O_3) grows in importance (Bonifácio & Diniz, 1994).

Types and mechanisms of tool wear

In machining processes, tool life is usually determined by using criteria based on tool wear (Carrilero et al., 2002). There are a few types of tool wear. Figure 2.3 shows the various types of tool wear commonly occurring in tool inserts. Among the various types of tool wear, only flank wear and crater wear are recognized as regular types that always occur (though at varying rates). Flank wear occurs on the flank face and the primary cutting edge along with its accompanying notch, and crater wear occurs on the rake face. The other types of wear, termed "irregular types," generally can be avoided by selecting the proper tool material and cutting conditions (Chouhury et al., 1999). Flank wear has also been long recognized as critical to the final surface quality in the finished machining (Ming, Xiahong, & Shuzi, 1999). For these reasons, most tool wear monitoring studies focus on flank and crater wear.

Several mechanisms are known to cause tool wear as a function of cutting temperature (Carrilero et al., 2002). Diffusion, erosion-abrasion, fatigue-plastic, corrosion, and adhesion are the most common wear mechanisms in various cutting temperatures. Erosion and adhesion cannot be avoided during the cutting process in any cutting temperature ranges. Adhesion wear involves the direct transfer of tool particles to metal chips. Additionally, the incorporation of microscopic fragments from the workpiece material into the tool surface cannot be ignored. These fragments are unstable mechanically; thus they can be removed from the tool surface by the action of the high strength cutting forces that are produced. In this process, the tool particles are worn away, causing tool wear (Kendall, 1995).

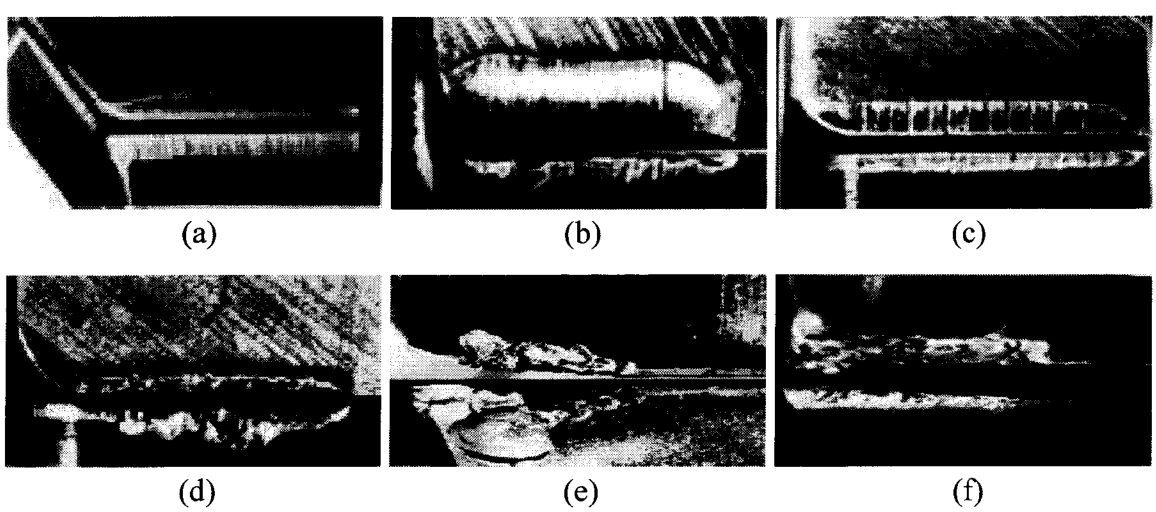


Figure 2.3. Type of wear: (a) flank wear; (b) crater wear; (c) thermal cracking; (d) chipping; (e) fracturing; (f) welding (Mitsubishi Materials Co., n.d.)

Signal Processing Methods

To utilize the information (or signal) obtained from the sensor mounted on a cutting tool (e.g., a CNC turning machine in this study), a signal processing technique is required. Currently three categories of signal processing methods are used widely: the traditional method, Fourier transform, and Wavelet transform.

Traditional signal processing

The oldest and simplest way to record and analyze a signal is by recording it as a wave form in a time domain (such as .wav format in PC and music CD recoding). For this reason, it is called a time-series analysis. However, unlike the human senses (ears hear sound; eyes see color), traditional mechanical, chemical, and electronic sensors used in the contemporary laboratory environment cannot separate the signals into their basic components. For example, if a microphone is used to record the sounds of the cutting process, the sound signal captured by the microphone may include noise from the spindle motor, gear box, tool and material reaction, machine bearings, lubricant pump motor, and even reflections of those noises. Therefore, if a researcher intends to catch a specific sound component or frequency range during the machining process, traditional sound recording is not sufficient because traditional recording cannot filter the unwanted noise.

Fourier transformation

Human hearing responses to sound frequencies are well studied (Walker, 1999). It is clear that humans perceive tones of different frequency as having a different pitch; musical notes, for example, are called higher or lower depending on whether they have corresponding higher or lower frequencies. The mathematical analysis of the frequency content of signals is called Fourier analysis. The frequency content of a signal can be revealed by its Fourier transform, and its components are formed by a fast Fourier transform made possible by modern computer technology.

The Fourier transform of a signal $x(n)$ is a function $X(w)$. The original signal is in the time domain, and $X(w)$ is in the frequency domain. The time variable n is discrete, and the frequency variable w is continuous. $X(w)$ is 2π periodic because each exponential e^{inw} is 2π periodic:

$$X(w) = \sum_{n=-\infty}^{\infty} x(n)e^{-inw} . \tag{2.1}$$

Fourier analysis studies the connections between $x(n)$ and $X(w)$—in other words, how the properties of the signal are reflected in its transform. The inverse Fourier transform recovers $x(n)$:

$$x(n) = \frac{1}{2\pi} \int_{-\pi}^{\pi} X(w)e^{inw} dw \tag{2.2}$$

This formula synthesizes x by combining the complex exponentials. Also, $x(N)$ can be obtained by multiplying equation (2.1) by e^{iNw} and integrating from $-\pi$ to π. The integral of e^{-inw} times e^{iNw} is zero except when $n = N$, the integral of the case is 2π, leading to equation (2.2) (Strang & Nguyen, 1996).

Despite its ability to transcribe a signal successfully into the frequency domain, Fourier transform cannot always distinguish the information that the researcher expects, leading to results that are impractical and of low resolution (Xiaoli & Zhejun, 1998). Also, the required number of frequencies monitored is unknown and must be chosen by trial and error, which can cause an excessive amount of calculation (Al-Habaibeh & Gindy, 2001). For these reasons, researchers needed another tool capable of expressing a signal with its components with an efficient number of coefficients. Wavelet transform demonstrated the capability to fulfill these needs (Xialoli & Zhejun, 1998).

Wavelet transformation

Wavelets become a powerful and remarkably flexible tool in many scientific applications (Walker, 1999). The idea of wavelet signal processing is not much different from that of Fourier processing in terms of decomposing one signal into several, but it is known to require less computation (Chan & Liu, 1998; Tansel, Mekdec, & McLaughlin, 1995). Unlike Fourier processing (decomposing a signal into sinusoidal functions of the frequency domain), wavelet transform provides an alternative method for breaking a signal down into sub-signals or levels with different frequencies under each time domain. Therefore, through wavelet processing, any particular component of a signal can be identified from the scale and position of the wavelets onto which is decomposed (Al-Habaibeh & Gindy, 2001; Xiaoli & Zhejun, 1998). Wavelets are obtained by creating a family of functions derived from a single function (Daubechies, 1978). This system can be expressed by the following equation:

$$h^{(a,b)}(x) = |a|^{-1/2}\, h\left(\frac{x-b}{a}\right) \tag{2.3}$$

where a and b are the dilation and translation parameters and $h^{(a,b)}$ represents the family of wavelets obtained from the single h function by dilation and translations. The given data consist of the f function in the given x coordinate. After wavelet transformation, the original signal can be reconstructed using the following expression:

$$f = C\int\frac{da}{a^2}\int db\left\langle h^{(a,b)}, f\right\rangle h^{(a,b)} \tag{2.4}$$

where f is the original signal function and $\left\langle h^{(a,b)}, f\right\rangle$ are the inner products of the wavelet.

For every level, the number of wavelet signals used to construct the signal equals 2^n where n is the level number. Based on the above description, if the discrete wavelet transformation is considered, the basic function (scaling function), $\Phi(x)$, of a wavelet system can be calculated with the following recursive equation:

$$\Phi(x) = \sum_n c(n)\Phi(2x-n) \tag{2.5}$$

where $c(n)$ is the wavelet coefficient and n is the level number. The primary wavelet signal is calculated from the scaling function according to:

$$\Psi(x) = \sum_{n=0}(-1)^n c(n+1)\Phi(2x-n) \tag{2.6}$$

where $c(n+1)$ is the coefficient. Similarly, the original function can be reconstructed using the following equation:

$$f(x) = \sum_{n=-\infty}^{\infty} c(n)\Phi_n(t) + \sum_{i=0}^{\infty}\sum_{j=-\infty}^{\infty} d(i,j)\Psi_{i,j}(t) \tag{2.7}$$

where $c(n)$ and $d(i,j)$ are the coefficients of the wavelet transform. Daubechies (1978) proposed the values of the h functions as follows in the procedures of decomposition and reconstruction:

$$
\begin{aligned}
h(0) &= (1 \pm \sqrt{3})/(4\sqrt{2}) \\
h(1) &= (3 \pm \sqrt{3})/(4\sqrt{2}) \\
h(2) &= (3 \pm \sqrt{3})/(4\sqrt{2}) \\
h(3) &= (1 \pm \sqrt{3})/(4\sqrt{2})
\end{aligned}
\tag{2.8}
$$

The wavelet coefficients are found based on the above wavelet system, and each decomposed signal shows the characteristics of the original signals containing the condition of tool wear. However, to utilize the decomposed signals in a tool wear monitoring system, a decision-making system is necessary that classifies the amount of tool wear based on the information from the signals. Artificial Neural Networks (ANN) has been proposed as a decision-making system in tool condition monitoring systems (Chen & Jen, 2000; Choudhury, Jain, & Rao, 1999; Dimla Jr., Lister, & Leighton, 1998; Liu & Altintas, 1999; Niu, Wong, Hong, & Liu, 1998; Özel & Nadgir, 2002; Purushothaman & Srinivasa, 1994; Scheffer & Heyns, 2001; Silva, Reuben, & Wilcox, 1998; Tansel, Mekdeci, & McLaughlin, 1995; Venkatesh, Zhou, & Caudill, 1997; Zawada-Tomkiewicz, 2001). In the next section, the theoretical background and properties of ANNs are reviewed.

Artificial Neural Networks

Although the Artificial Neural Networks (ANNs) is fairly new technology, it has gained extreme popularity in the intelligent manufacturing system (IMS) industry and financial area because of its classification and optimization capabilities (Dimla Jr., Lister, & Leighton, 1997; Raj et al., 2000). After ANN technology was introduced in the 1950s, a great number of studies were carried out to develop enhanced ANNs. Some significant research has led to significant developments in ANN technology, including multi-layer (ML) networks, the back-propagation (BP) algorithm, Hopfield networks, adoptive resonance theory (ART), and the self-organizing method (SOM).

Different ANNs have unique structures, node connections, and mathematical learning algorithms. Each node is described by differences or differential equations. The nodes are interconnected between layers or within a layer. Each node in the layer receives the inner product of connection weights, with outputs of nodes in the previous layer. The inner product is called the activation value. Figure 2.4 shows the activation of a neuron. When the activation is given as the input to a neuron, the output of the same neuron should lie in the closed interval [0, 1]. For this, the sigmoid function has been used widely to squash the activation value. ANNs need at least one training rule that adjusts the weights of the connections among its nodes.

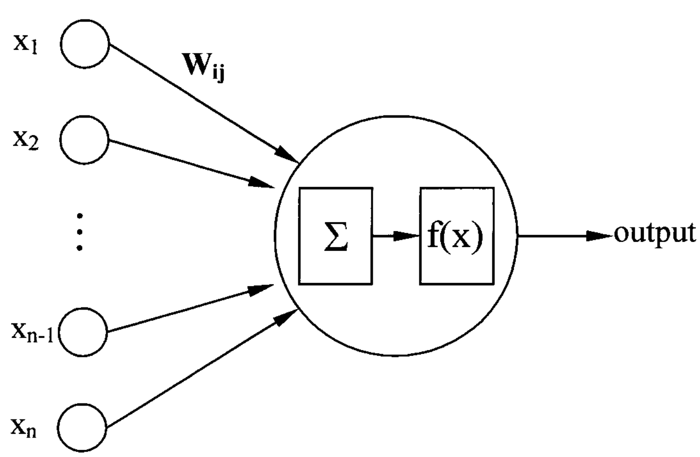


Figure 2.4. Operation of a neuron

The back-propagation (BP) algorithm is a multi-layer network algorithm that is used widely as a learning algorithm in ANNs because it is simple and has a comparably fast convergence speed during the training procedure. The BP algorithm works on a gradient descent method (Purushothaman & Srinivasa, 1998). For each training datum presented to the input layer of the networks, the error at the nodes in the output layer of the network is calculated. The BP algorithm refers to the propagation error of the nodes from the output layer to the nodes in the hidden layers. These errors are used to update the weights of the networks. The amount of weights to be added to the previous weights is calculated by the delta rule.

Also known as the Least Mean Square (LMS) method, the delta rule is one of the most commonly used learning rules (Purushothaman & Srinivasa, 1998). The main concept of the delta rule is that, for a given input vector, the output vector is compared to the correct answer. If the difference is zero, no learning takes place; otherwise, the weights are adjusted to reduce this difference. The following steps are involved in training the ANNs using a BP algorithm:

Step 1. The weights and thresholds are initialized randomly between layers. The value of weights and thresholds is usually recommended to be in the range of [0.25 ~ 0.45] to stabilize conversion during the training.

Step 2. The input pattern X is presented to the input layer and the outputs of neurons x_i are composed by:

$$x_i = \frac{1}{1+\exp(\sum W_{ij} x_i + \Theta_i)} \tag{2.3}$$

where W_{ij} represents the weights between layers and Θ_i represents the thresholds of the neurons.

Step 3. The error *E(p)* of a pattern is calculated by:

$$E(p) = \tfrac{1}{2}\sum \left(d_i(p) - x_i(p)\right)^2 \qquad (2.4)$$

and the mean squared error (MSE) for all the patterns in an iteration is calculated by:

$$E = \sum E(p) \qquad (2.5)$$

where p is the pattern number and d_i is the desired output.

Step 4. The error δ for each node in the output layer is computed by:

$$\delta_i(output\,layer) = x_j(1 - x_j)(d_i - x_i) \qquad (2.6)$$

Step 5. The weights between layers W_{ij}, and thresholds Θ_i in the layers are updated by:

$$W_{ij}(p+1) = W_{ij}(p) + \eta\delta_j x_i + \alpha(W_{ij}(p) - W_{ij}(p-1)) \qquad (2.7)$$

$$\Theta_i(p+1) = \Theta_i(p) + \eta\delta_i + \alpha(\Theta_i(p) - \Theta_i(p-1)) \qquad (2.8)$$

where η is learning factor and α is momentum or acceleration factor.

Step 6. The error δ for the nodes in the hidden layers is calculated by:

$$\delta_i(hidden\,layer) = x_i(1 - x_i)\sum \delta_j W_{ij} \qquad (2.9)$$

Step 7. For each training pattern, steps 5 and 6 are repeated until the input layer is reached.

Step 8. Steps 2 through 7 are repeated for the remaining training patterns until the specified criterion is reached, at which point the training of the network is stopped.

In the next section, researches into a tool wear monitoring system are reviewed. This review includes sensor and signal processing technologies adopted by researchers. Turning operation, tool wear, and signal process technologies are reviewed by focusing on the development of a tool wear monitoring system.

Studies of Tool Condition Monitoring

Tool condition monitoring (TCM) methods can be categorized into several groups based on how they monitor tool conditions. In-process TCM studies detect the amount of tool wear during the cutting process. Off-process TCM studies detect the amount of tool wear at the end of the cutting process. Some studies proposed the concept of on-line and off-line systems instead of in-process and off-process system, but many studies involving "on-line" systems are actually describing in-process systems. By definition, on-line systems are performed after the cutting process is finished while in-process systems monitor the tool condition during the cutting process. Some studies used the term "real-time" to describe what was, in effect, an in-process system (Li, 2001a; Li, 2001b; Liu & Altintas, 1999). The focus of this study is an in-process TCM system.

TCM systems also may be categorized into direct systems and indirect systems, based on the type of sensor technology used. Direct systems collect information or signals from the tool itself. A number of studies using optical sensors (e.g., CCD camera, LASER, SEM, optical fiber, etc.) showed the accuracy of the information directly related with amount of tool wear. However, these studies were limited because they could not be used in-process and are affected greatly by the presence of other materials, such as coolant and debris, or light sources on the tool. Therefore, direct systems have no benefit for use in the proposed TCM system in non-laboratory environments. In contrast, indirect systems sense secondary details of the cutting process (e.g., cutting forces, machining vibrations, acoustic emission signals, feed or spindle motor currents, temperatures, etc.) to determine tool condition. Indirect systems are optimal for integration into in-process tool condition monitoring systems; however, indirect systems require additional processes to determine the relationship between the signals and the amount of tool wear, which often is non-linear.

Indirect sensing systems rely on sensors, among which the dynamometer sensor has achieved the greatest correlation with tool conditions. However, the dynamometer is limited because, when it is installed, it may affect the tool capability. In addition, the dynamometer is limited because of its high cost and lack of overload protection (Li, 2001b).

Acoustic emissions also have been used in TCM studies. However, acoustic emission is limited as a sensing technology because noise contamination interferes with accurate data collection (Dimla Sr., 2000). To overcome the limitations of sensor technologies, many studies have proposed the use of multi-sensors to establish a stronger correlation between indirect signals and actual tool condition (Chen & Jen, 2000; Chongchoo & Saini, 2002; Quan et al., 1998; Schefer & Heyns, 2001; Silva et al., 1998; Yeo et al., 2000). An alternative example of a multi-sensor system is to study the current signals of feed motor and spindle motor (Li, 2001b; Li & Tso, 1999; Stein & Huh, 2002). These studies showed that multi-sensor systems could provide additional signals for better prediction results. However, the distribution of different weights to each signal brought more complexity to the TCM system. Table 2.1 summarizes sensor technologies adopted by other studies.

No matter which sensor technology is adopted, a decision-making system that can judge or predict the amount of tool wear is required for the indirect TCM system. Several

Table 2.1. Major sensor techniques in TCM studies from the last decades

Methods	Investigator	Year	Sensor	Process
Optical	Bouzakis, Michailidis, Vidakis, & Efstathio	2001	SEM	Turning (off-line)
	Brdley & Wong	2001	CCD & Stylus	Milling (off-line)
	Choudhury, Jain, & Rao	1999	Optical fiber	Turning (on-line)
	Karthik, Chandra, Ramamoorthy, & Das	1997	CCD	Turning (off-line)
	Kassim, Mannan, & Jing	2000	CCD	Turning (off-line)
	Lanzetta	2001	CCD	Turning (off-line)
	Zawada-Tomkiewicz	2001	CCD	Turning (off-line)
Force	Astahov	1999	Dynamometer	Turning (off-line)
	Balazinski, Czogala, Jemielinak, & Leski	2002	Dynamometer	Turning (off-line)
	Chen	2000	Dynamometer	Milling (off-line)
	Choudhury & Kishore	2000	Dynamometer	Turning (off-line)
	Davim & Baptista	2000	Dynamometer	Milling/Drill (off-line)
	Deyuan, Yuntai, & Dingchang	1995	Dynamometer	Milling (on-line)
	Donovan & Scott	1995	Electro motive force transducer	Turning (on-line)
	Ertune & Loparo	2001	Dynamometer	Drill (off-line)
	Grabec, Govekar, Susič, & Antolovič	1998	Dynamometer	Turning (off-line)
	Hong, Rahman, & Zhou	1996	Dynamometer	Turning (off-line)
	Kashimura	1986	Dynamometer	Drill (off-line)
	Ko & Kim	2001	Dynamometer	Turning (off-line)
	Koren, Ko, Ulsoy, & Danai	1991	Dynamometer	Turning (on-line)
	Lee, Kim, & Lee	1998	Dynamometer	Turning (off-line)
	Li, Lau, & Zhang	1992	Dynamometer	Drill (in-process)
	Liu & Altintas	1999	Dynamometer	Turning (on-line)
	Obikawa, Kaseda, Matsumura, Gong & Shirakashi	1996	Dynamometer	Turning (off-line)
	Özel & Nadgir	2002	Dynamometer	Turning (off-line)
	Purushothaman & Srinivasa	1998	Dynamometer	Turning (off-line)
	Szecsi	1998	Dynamometer	Turning (off-line)
	Tansel, Mekdeci & McLaughlin	1995	Dynamometer	Milling (off-line)
	Venatesh, Zhou & Caudill	1997	Dynamometer	Turning (off-line)
	Zhou, Anderson & Ståhl	1997	Dynamometer	Turning (off-line)
Vibration	Bonifácio & Diniz	1994	Accelerometer	Turning (off-line)
	Jun & Suh	1999	Accelerometer	Milling (off-line)
	Li, Dong & Venuvinod	2000	Accelerometer	Milling (off-line)
	Ming, Xiahong & Shuzi	1999	Accelerometer	Milling (off-line)
	O'Donnell, Young, Kelly & Byrne	2001	Accelerometer	Drill (off-line)
	Wu & Du	1996	Accelerometer	Drill (off-line)
Acoustic	Al-Habaibeh & Gindy	2001	Acoustic Emission	Milling (off-line)
	Liang & Dornfeld	1989	Acoustic Emission	Turning (off-line)

Table 2.1. Major sensor techniques in TCM studies from the last decades (continued)

Methods	Investigator	Year	Sensor	Process
Acoustic	Nayfeh, Eyada, & Duke	1995	Ultrasonic	Turning (on-line)
	Niu, Wong, Hong, & Liu	1998	Acoustic Emission	Turning (off-line)
	Xiaoli & Zhejun	1998	Acoustic Emission	Milling (off-line)
Multi-sensors	Chen& Jen	2000	Dynamometer & Accelerometer	Milling (off-line)
	Chongchoo & Saini	2002	Acoustic Emission & Dynamometer	Turning (on-line)
	Das, Bandyopadhyay, & Chattopadhyay	1997	Dynamometer & Accelerometer	Turning (off-line)
	Dimla, Lister, & Leighton	1998	Dynamometer & Accelerometer	Milling (off-line)
	Dimla & Lister	2000	Dynamometer & Accelerometer	Turning (on-line)
	Kuo	2000	Dynamometer, Accelerometer, & Acoustic Emission	Turning (on-line)
	Kwon & Ehmann	1994	Dynamometer & Accelerometer	Turning (off-line)
	Quan, Zhou, & Luo	1998	Acoustic Emission & Current meter	Milling/Turning (off-line)
	Scheffer & Heyns	2001	Strain sensor & Accelerometer	Turning (on-line)
	Silva, Reuben, & Wilcox	1998	Strain sensor, Microphone, Current meter, & Accelerometer	Turning (off-line)
	Yeo, Khoo, & Neo	2000	Dynamometer & Colorimeter	Turning (off-line)
Miscellaneous	Henry	2002	Contact & Chemical	Turning (off-line)
	Kim & Chun	1999	Current	Milling (on-line)
	Kim, Lee, & Sin	1999	None	Turning (off-line)
	Li & Tso	1999	Current meter	Drill (off-line)
	Li	2001a	Touch sensor	Turning (real-time)
	Li	2001b	Current sensor	Turning (real-time)
	Li, Venuvinod, Djorjevich, & Liu	2001	Touch sensor	Turning (off-line)
	Maropoulos & Alamin	1996	None	Turning (off-line)
	Stein & Huh	2002	Current meter	Turning (on-line)
	Tseng & Chou	2002	Motor workload	Milling (on-line)

approaches to decision-making systems have been adopted in TCM studies. The oldest method is based on a mathematical model proposed by several studies (Ertune & Loparo, 2001; Koren et al., 1991; Kwon & Ehmann, 1994; Li, 2001b; Liang & Dornfld, 1989; Zhou et al., 1997).

Mathematical models provide a comparably easier method that can be adopted in the TCM system, but often the mathematical model cannot explain unknown factors of the tool wear mechanism. The statistical model is another system that has been used in TCM studies for many years (Davim & Baptista, 2000; Donovan & Scott, 1995; Jennings & Drake, 1997; Jun & Suh, 1999; Li & Tso, 1999; Nayfeh et al., 1995; Szecsi, 1998). From systematic experimental data, a relationship function between the amount of tool wear and signal data is built. However, the relationship function developed by the statistical method is often a linear model. Therefore, it cannot explain non-linearity between dependent and independent variables. These linear statistical models were developed in conjunction with off-process TCM systems.

Other technologies adopted as in-process decision-making systems include artificial neural networks (ANN) and fuzzy logic systems. A combined model of those two systems, fuzzy-neural networks (FNN), has been used in various studies. Unlike mathematical or statistical models, the ANN system can learn from the obtained data and continually update its accuracy. The FNN system gains an advantage due to the learning capability of the neural networks and the expert systems of fuzzy logic. As a result, the FNN system has a shorter learning time than systems that employ an ANN alone (Balazinski et al., 2002; Chen, 2000; Chongchoo & Saini, 2002; Kuo, 2000; Li et al., 2000). Various methods to combine these two systems have been proposed, and the results vary depending on the applications used (Li et al., 2000). Table 2.2 summarizes the decision-making systems used in TCM studies. From the survey of TCM studies from the last decades, most TCMs that have been developed in research cannot be implemented successfully because inadequate sensor information and machining process models have

Table 2.2. Major decision-making systems in TCM studies of the last decades

Methods	Inspectors	Year	Scheme	Signal process
Neural Networks	Al-Habaibeh & Gindy	2001	Self-learning Algorithm	Fast Fourier Transformation (FFT)
	Chen & Jen	2000		Time-series
	Choudhury et al.	1999	Backpropagation (BP)	
	Das, Bandyopadhyay, & Chattopadhyay	1997	BP	Time-series
	Dimla, Lister, & Leighton	1998	Feed-forward multi-layer	FFT
	Hong, Rahman, & Zhou.	1996	BP	Wavelet decomposition (WT)
	Lee & Lee	1999	error-Backpropagation	Time-series
	Liu & Altintas	1999	BP	Time-series
	Niu, Wong, Hong, & Liu.	1998	Adaptive resonance theory (ART2)	Time-frequency pattern, Wavelet packet decomposition (WPD)
	Obikawa, Kaseda, Matsumura, Gong, & Shirakashi.	1996	BP, Auto-regressive (AR)	FFT
	Özel & Nadgir	2002	BP	Time-series
	Purushothaman & Srinivasa	1994	BP	Time-series
	Quan, Zhou, & Lou.	1998	BP	Time-series
	Scheffer & Heyns	2001	Self-organizing map (SOM)	FFT, WPD
	Silva, Reuben, Baker, & Wilcox.	1998	SOM	Time-series, FFT
	Tansel, Mekdeci, & MLaghlin.	1995	ART2	FFT, Wavelet transform
	Venkatesh, Zhou, & Caudill	1997	BP	Time-series
	Yeo, Khoo, & Neo.	2000	BP	Time-series
	Zawada-Tomkiewicz	2001	Levenberg-Marquardt learning rule	Image processing
Fuzzy Logic	Li	2002	Fuzzy classifier, Pattern classification, Group method of data handling (GMDH), Polynomial learning network (PLN), BP	Time-series, Fourier transform (FT), Short-time Fourier transform (STFT), Wavelet transform
	Ming, Xiaohong, & Shuzi.	1999	Generic algorithm (GA) learning	Time-series
	Xiaoli & Zhejun	1998	Fuzzy clustering method	Time-series
Fuzzy Neural Networks	Balazinski, Czogala, Jemielniak, & Leski	2002	Center of Gravity (COG), BP	Time-series
	Chen	2000	Fuzzy-net training scheme	Time-series
	Chungchoo & Saini	2002	Least-square Backpropagation (LSBP)	Time-series
	Kuo	2000	Kohonen's feature mapping, error-Backpropagation, Counterpopagation	Time-series, FFT
	Li, Dong, & Venuvino	2000	BP	FFT
Statistical	Bonifácia & Diniz	1994		FFT
	Choudhury & Kishore	2000	Correlation	Time-series
	Davim & Baptista	2000	Regression	
	Donovan & Scott	1995	Regression	FFT
	Jennings & Drake	1997	Statistical Quality Control (SQC)	Time-series

Table 2.2. Major decision-making systems in TCM studies of the last decades (continued)

Methods	Inspectors	Year	Scheme	Signal process
Statistical	Jun & Suh	1999	SQC	Time-series
	Ashimura	1986	Correlation	Time-series
	Kassim, Mannan, & Jing	2000	Run-length statistical method	Image processing
	Lee, Kim, & Lee	1998	ANOVA	Time-series
	Li & Tso	1999	Regression	Time-series
	Nayfeh, Eyada, & Duke	1995	Regression	Time-series
	Szecsi	1998	Regression	Time-series
Mathematical	Ertune & Loparo	2001	Decision fusion center algorithm	Hidden Markov, phase plane, transient time, model-based torque predicting
	Koren, Ko, Ulsoy, & Danai	1991	Standard estimation algorithm	Time-series
	Kwon & Ehmann	1994	Separate imaginary transfer function	FFT
	Li	2001	Park & Ulsoy model	Time-series
	Liang & Dornfeld	1989	Autoregressive (AR) time series model, Stochastic gradient algorithm	Time-series
	Tseng & Chou	2000	Load %	Time-series
	Wu & Du	1996	Wavelet packet feature extraction	WP, FFT
	Zhou, Anderson, & Ståhl	1997	Maximum stress distribution model	Time-series

been utilized that did not reflect the process complexity satisfactorily (Dimla Sr., 2000). To achieve an in-process TCM, certain challenges must be overcome. Some studies have highlighted the importance of eliminating noise factors during signal processing (Dimla Sr., 2000; Li, 2002). In addition, the major disadvantage of neural networks (lack of protection from an insufficient learning source) also needs to be overcome before TCMs can be implemented successfully (Dimla Jr. et al., 1997). Some studies approached this problem by applying wavelet decomposition techniques (Hong et al., 1996; Li, 2002; Niu et al., 1998; Schefer & Heyns, 2001; Wu & Du, 2000). However, most studies utilized only noise elimination functions or classification based on different frequency ranges. Therefore, the studies could not show a strong relationship between tool condition and decomposed elements of the signals collected by the sensors.

This literature review has demonstrated a need for a new TCM system that can provide accurate information using modern sensing and signal processing technologies. To this end, the next chapter proposes an experimental methodology for developing a new TCM system, including data analysis for developing a TCM system.

CHAPTER 3. EXPERIMENTAL SETUP AND DESIGN

This chapter introduces the experimental setup and design for the TCM system. The experimental setup encompasses the hardware and software systems and their setup, and shows the machining parameters and tool conditions considered in the experiments. Figure 3.1 shows the schematic illustration of the experimental setup.

Machine and Sensor Setup

This section introduces the hardware adopted for this study, including the CNC machine, sensors, and their setup. Mechanical properties of the cutting tools and the workpiece are also presented.

CNC lathe machine and insert tools

The following sub-sections highlight the specifications of the machine and the machining parameters. These specifications can significantly impact the tool life and the machine vibration, as will be explained along with the properties of the cutting tool utilized in this experiment.

CNC lathe machine

The TCM system discussed in this research utilized a Clausing/Colchester Storm model A500 CNC lathe. The CNC machine was prepared in the CNC laboratory of the Department of Industrial Education and Technology at Iowa State University, and was equipped with a GE *Fanuc* controller for precise turret motion and spindle speed control. The machine can be operated in manual, semi-automatic, or fully automatic modes. It has ±0.0002" position

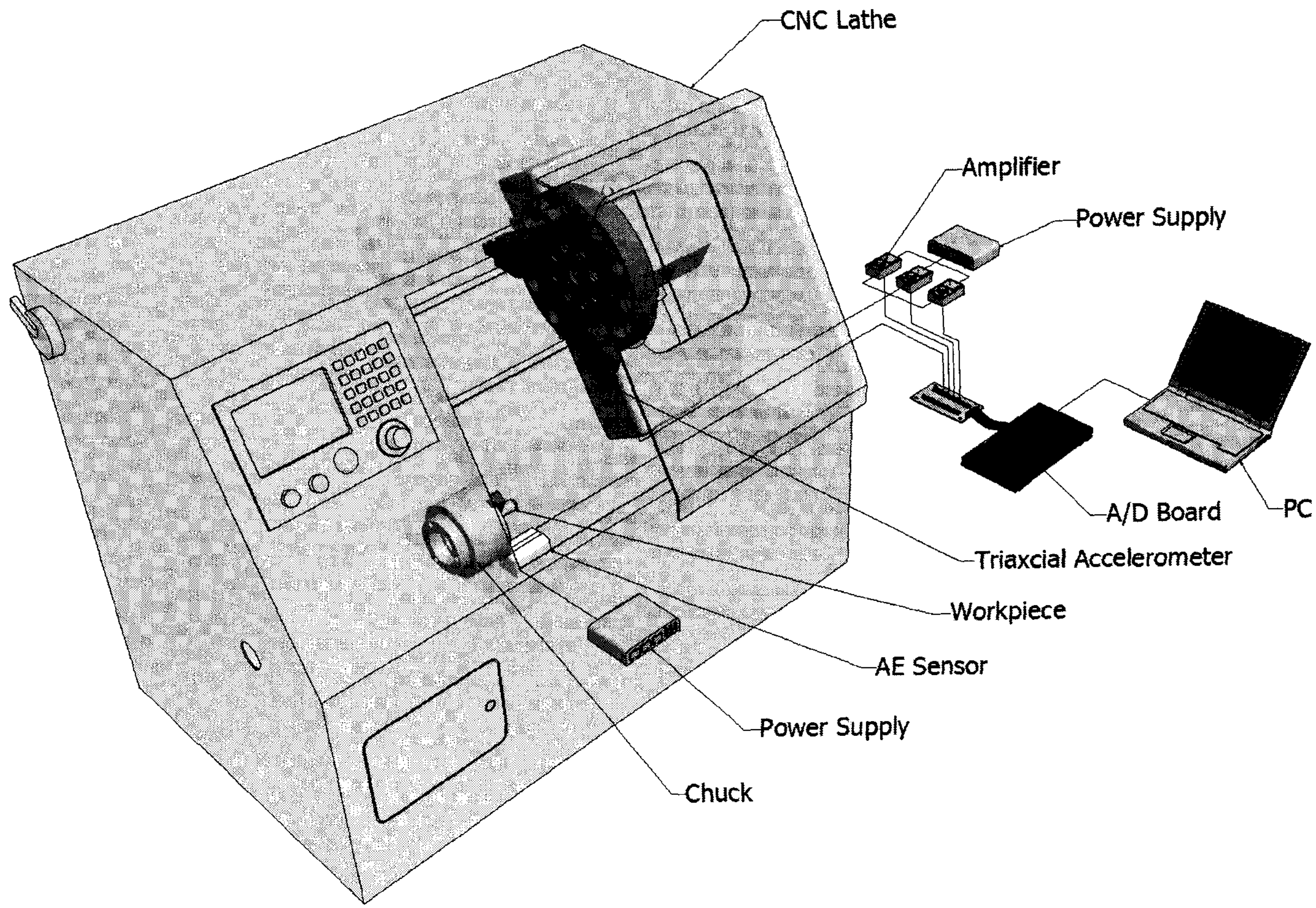


Figure 3.1. Experiment Setup

accuracy and ±0.00008" repeatability during the cutting process when it is operated with a NC program. Appendix A shows the NC program developed for this experiment. The machine is a right-hand machine equipped with a turret that can hold up to 12 tools simultaneously, and has a maximum spindle speed of 4,000 rpm and 7.5 HP spindle motor power. The maximum travel length is 13.78" in the longitudinal direction, and the maximum travel diameter is 6.69" in the diagonal direction.

There are three directions of vibration measured in this experiment: the positive x (+X) direction, defined as the radial direction from the center of the workpiece to the tool tip; the positive z (+Z) direction, defined as the longitudinal direction from the workpiece holder to the tool holder; and the positive y (+Y) direction, the tangential direction, which was assigned using the right-hand rule. This study employed the straight cut (a major cutting type in turning operations), with hardware setup that includes a general-purpose indexable insert tool, a befitted shank, and the tool holder for the indexible insert tool. To ensure a stable cutting operation, the cutting tool was aligned with a radial line of the workpiece.

Machining parameters and properties

Machining parameters are defined based on the combination of the workpiece material and cutting tool. Appropriate parameters are recommended by the machine tool manufacturer to ensure the quality of the product and the life of the machine. Cutting harder materials requires more power and generates more heat in the nose (hot spot) of the cutting tools. To operate the cutting tool without failure within the expected running time, the cutting speed must be kept under the recommended speed. This helps to maintain the cutting temperature within the limitations of the tool. For this reason, workpiece hardness often is an easy means to determine the cutting speed. Additionally, changes to the microstructure of a workpiece can alter the results of cutting even if the material hardness is kept consistent.

The cutting conditions are the combination of spindle speed, feed rate, and depth of cut during machining. Since each parameter has a limited range, based on the specifications of the machine, a proper combination of the parameters has to be chosen before cutting. Selecting the appropriate cutting conditions also involves considering the life of the tool. Tool life is defined as the amount of time it takes for tool wear to reach certain, predetermined levels (Oberg et al., 2000). Therefore, optimizing the performance and life of the tool requires proper setup of the cutting conditions. Optimizing the machining condition requires considering the depth of cut based on the workpiece material, maximum power of the machine, and tool and machine rigidity (Yellowley & Gunn, 1989). Choosing a certain depth of cut allows the feed rate to be calculated within the limit of machine power. Spindle speed then can be decided to obtain the optimized life of the tool.

In this study, a general range of spindle speed, feed rate, and depth of cut were chosen with combinations of the tools that have different amounts of wear. Machining behavior was determined by signals captured by two sensors (a tri-axial accelerometer and an acoustic emission [AE] sensor) under different combinations of tools and machining conditions. The machining parameters used in this study are discussed in the experimental design section.

Insert tools used in the experiment

A number of different indexible insert tools are available in the market today, with various materials, surface treatments, and geometric designs. High-speed steel (HSS) tools are used most commonly for drilling and milling. Cemented carbide is common in insert tools, and is available in four types depending on its alloy materials and surface treatment. Diamond Cutting Tools are recommended for rapid cutting, and Chemically Vapor-Deposited (CDV) carbide is the most advanced tool developed after the diamond-cutting tool. Cubic Boron Nitride (CBN) tools are the hardest tools available. Geometric differences between tools, such as tool nose, relief angle, and chip breaker, provide unique cutting characteristics (Fang, 1998).

This study utilized a carbide insert tool (CNMG-432) from Mitsubishi Materials Corporation. The tool had a rhombic 80° shape, 0° clearance angle, M class (±0.003") tolerance, G-type groove shape, 1/2" inner circle size, 3/16" thickness, 1/32" tool nose, and a general, cheap breaker shape. Figure 3.2 provides a schematic diagram of the geometric characteristics of the insert tool used. To improve rigidity and cutting performance, the tool had three layers of coating: titanium carbide nitrite (TiCN), aluminum oxide (Al_2O_3), and titanium nitrite (TiN). The tool had a wide range of cutting speeds, and was designed to perform several different types of cutting processes, including straight turning, face turning, and face milling in rough and finish cuts (Mitsubishi Materials Co., n.d.).

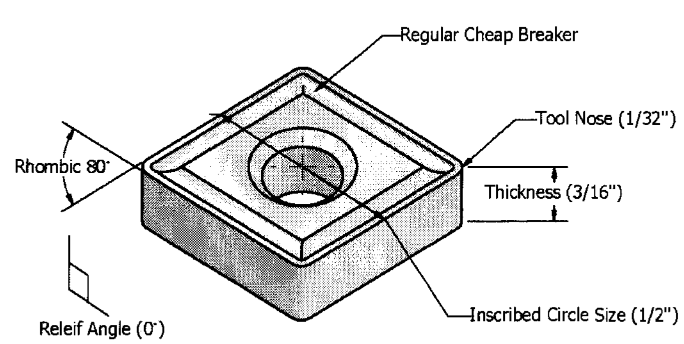


Figure 3.2. Insert tool employed in experiment

In this study, a straight turning cut was performed with various spindle speeds, feed rates, and cutting depths. A number of worn tools used in the machine workshop were provided by a machining manufacturer in Ames, Iowa and Mitsubishi Materials Corporation.

Workpiece characteristics

The workpiece employed in this experiment was an aluminum 6061 alloy cylinder. Aluminum 6061 is used in many applications, such as aircraft fittings, camera lens mounts, electrical fittings and connectors, brake pistons, hydraulic pistons, valves and valve parts, and bicycle frames. It has excellent joining characteristics, and good acceptance of applied coatings. It has combined characteristics of high strength, good workability, and high resistance to corrosion. Table 3.1 shows the general composition of Aluminum 6061 alloy, and Table 3.2 shows its physical and mechanical properties (ASM International, 1990; Holt & Ho, 1996).

The aluminum material also was assumed to cause minimal tool wear during the cutting process, meeting the assumption that there would be no significant differences in the amount of tool wear among the specimens collected under the same tool conditions. The total cutting length was 1", and the vibration and acoustic emission (AE) signals acquisition program was used to collect data from the point where the tool tip reached to 0.5" from the edge of the material.

Sensor setup

The TCM system employed two sensors: a tri-axial accelerometer to measure vibrations during the cutting process, and an AE sensor to detect the signal related to the energy released from the workpiece during the cutting process. Ideally, the sensor detects

Table 3.1. Composition table of aluminum 6061 alloy

Component	Weight %	Component	Weight %	Component	Weight %
Aluminum [Al]	95.8 – 98.6	Magnesium [Mg]	0.8 – 1.2	Zinc [Zn]	Max 0.25
Chrome [Cr]	0.04 – 0.35	Mangham [Mn]	Max 0.15	Other, each	Max 0.05
Cupper [Cu]	0.15 – 0.4	Silicon [Si]	0.4 – 0.8	Other, total	Max 0.15
Iron [Fe]	Max 0.7	Titanium [Ti]	Max 0.15		

Table 3.2. Properties of aluminum 6061 alloy

Properties	Metric	English	Comments
Density	2.7 g/cc	0.0975 lb/in^2	
Brinell Hardness	95	95	500G load; 10 mm ball
Ultimate Tensile Strength	310 Mpa	45000 psi	
Tensile Yield Strength	276 Mpa	40000 psi	
Poison's Ratio	0.33	0.33	
Fatigue Strength	96.5 Mpa	14000 psi	
Shear Strength	207 Mpa	30000 psi	
Melting Point	582 – 652 °C	1080 - 1205 °F	

only vibrations generated by interactions between the cutting tool and the workpiece, but undesired integrations of the signals generated from other sources (e.g., spindle motor, hydraulic pump, and feed motors) cannot be avoided. The methodology of separating the desired signal from the raw signals is discussed in the signal process section of Chapter 4.

Principle of the accelerometer

The basic element of many vibration-measurement instruments is the seismic unit that provides information of the relative displacement with its fixture. Figure 3.3 shows a schematic diagram of a typical accelerometer. Depending on the frequency range utilized in the experiment, the amount of displacement, velocity, or acceleration is indicated by the motion of the suspended mass with respect to the unit case.

To determine the behavior of such instruments, the motion of mass (*m*) can be considered as equation 3.1:

$$m\ddot{x} = -c(\dot{x} - \dot{y}) - k(x - y), \tag{3.1}$$

where *k* is the spring coefficient, *c* is the damper coefficient, and *x* and *y* are the displacement of the seismic mass and the vibrating body, respectively, both measured with respect to an inertial reference (Thomson, 1993). If the relative displacement (*Z*) of the mass (*m*) and the case are attached to the vibrating body, then:

$$z = x - y. \tag{3.2}$$

Assuming the sinusoidal motion of $y = Y \sin \omega t$ of the vibrating body, the following equation can be obtained:

$$m\ddot{z} + c\ddot{z} + kz = m\omega^2 Y \sin \omega t \tag{3.3}$$

If the steady state solution $z = Z \sin(\omega t - \phi)$ is adopted, the equations obtained are:

$$Z = \frac{m\omega^2 Y}{\sqrt{\left(k - m\omega^2\right)^2 + (c\omega)^2}} = \frac{Y\left(\frac{\omega}{\omega_n}\right)^2}{\sqrt{\left[1 - \left(\frac{\omega}{\omega_n}\right)^2\right]^2 + \left[2\zeta\frac{\omega}{\omega_n}\right]^2}} \tag{3.4}$$

and

$$\tan\phi = \frac{\omega c}{k - m\omega^2} = \frac{2\zeta\frac{\omega}{\omega_n}}{1 - \left(\frac{\omega}{\omega_n}\right)^2} \tag{3.5}$$

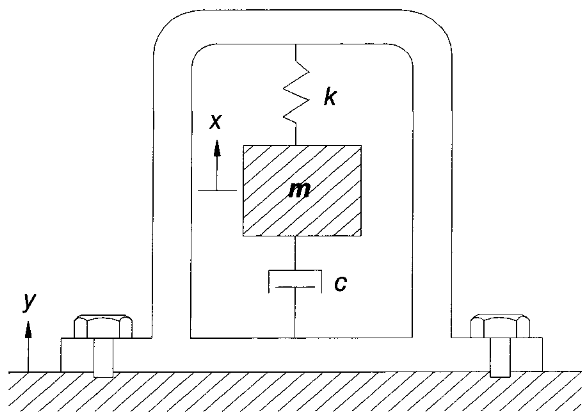


Figure 3.3. Schematic illustration of a typical accelerometer (Thomson, 1993)

where Z is relative displacement. It is evident that the parameters involved are the frequency ratio ω / ω_n and the damping factor ζ. The type of instrument is determined by the useful range of frequencies with respect to the natural frequency ω_n of the instrument (Thomson, 1993). When the natural frequency of the instrument is high compared to that of the vibration measured, the instrument indicates acceleration. Then, the factor

$$\sqrt{\left[1-\left(\frac{\omega}{\omega_n}\right)^2\right]^2+\left[2\zeta\frac{\omega}{\omega_n}\right]^2}$$

approaches unity for $\omega / \omega_n \rightarrow 0$, such that:

$$Z=\frac{\omega^2 Y}{\omega_n^2}=\frac{acceleration}{\omega_n^2} \tag{3.6}$$

Thus, Z becomes proportional to the acceleration of the motion to be measured by a factor $1/\omega_n^2$. Electromagnetic accelerometers generally utilize damping around $\zeta = 0.7$, which not only extends the useful frequency range, but also prevents phase distortion for complex waves. On the contrary, high natural frequency instruments, such as the piezoelectric crystal accelerometers, have near-zero damping and operate without distortion up to frequencies of 0.06 f_n (Thomson, 1993).

Accelerometer employed in this experiment

The significant relationship between tool conditions and vibrations during machining is well recognized, and the comparably low noise implication of the vibration sensors is discussed in other TCM studies (Bonifácio & Diniz, 1994; Dimla Sr., 2000; Jun & Suh, 1999). Among the several vibration detection techniques, piezoelectric accelerometers are often adopted for tool wear studies for measuring high-frequency vibrations (Thomson, 1993). These instruments rely on the piezoelectric effect of quartz or ceramic crystals to generate an electronic output related with acceleration. The piezoelectric effect produces an opposed accumulation of charged particles on the crystal. This charge is proportional to an applied force or stress. A force applied to a quartz crystal lattice structure alters alignment of positive or negative ions, which results in an accumulation of these charged ions on the opposing surface. These charged ions accumulate on an electrode that is ultimately conditioned by transistor microelectronics. Piezoelectric accelerometers are applicable to a variety of mechanical configurations defined by the nature of the inertial force of an accelerated mass acting upon the piezoelectric material. Among the several accelerometer configurations being used, such as shear mode, flexural mode and compression mode, a tri-axial shear mode sensor was employed to acquire simultaneously the three directions of vibration signals: radial (x), tangential (y), and longitudinal (z). A 356B07 model from PCB Piezotronics was employed for the tri-axial accelerometer. Its sensitivity is 100 mV/g and it has 3 ~ 5,000 Hz frequency range. This sensor utilizes shear mode ceramic sensing elements.

The accelerometer mounting position in turning operations has been proposed by a number of studies (Dimla Jr., Lister, & Leighton, 1998; Huang et al., 1999; O'Donnell et al., 2001; Schefer & Heyns, 2001). In this study, the sensor was mounted under the shank, determined to be an efficient position to detect the vibration from the cutting tool. After the mounting position was decided, a thread hole was cut in the shank, and a thread pin was installed to connect the sensor and the shank. The thread hole and pin prevent excessive vibrations generated by the interaction of the shank and the sensor. Between the sensor and the shank, an additional wax-based protective material was applied to provide an evenly layered surface. It is also expected to help to avoid direct contact between the accelerometer housing and the shank to prevent damage to the sensor. Figure 3.4 shows the schematic diagram of the accelerometer, how it is mounted on the shank, and the assigned direction for signals.

The vibrations signals from each direction were sent to an amplifier first to provide proper signal strength for signal processing in an analog-digital (A/D) converter (DaqBook 100 model from IOTech). Each amplifier was powered by an external power source so that a stable amplification was assured during the experiments. Three 480E03 PCB battery-powered sensor signal conditioners were used as amplifiers, powered by a Tektronix CPS250 power supply. The sensor signal conditioner had a response range of 0.75 ~ 100,000 Hz with 1, 10, 100 voltage gain options and ±10 volts maximum output range.

Acoustic emission signals

Acoustic emission (AE) refers to the generation of transient elastic waves during the rapid release of energy from localized sources within a material. The source of these

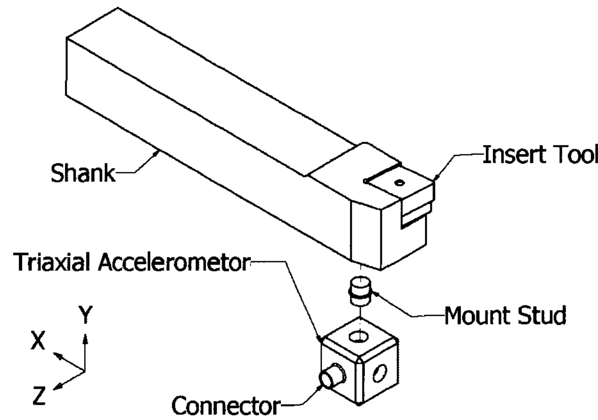


Figure 3.4. Schematic diagram of sensor mount and signal directions

emissions in metals is closely associated with the dislocation movement accompanying plastic deformation and the initiation and extension of cracks in a structure under stress (ANSI/ASTM E610-77). Other sources of acoustic emission include: melting, phase transformation, thermal stresses, cool down cracking, and stress build up. Dornfeld (1989) classified the source of acoustic emission during metal the cutting process into the following categories: (a) plastic deformation of a workpiece, (b) plastic deformation of the chip, (c) frictional contacts of workpiece and tool having flank wear and crater wear, (d) collisions between chip and tool, (e) chip breakage, and (f) tool fracture. In recent years, AE instruments have been adopted for use in structure integrity evaluation, non-destructive testing, and quality testing for advanced material industries (Li, 2002). AE was also proposed as a possible signal source to detect the tool condition in a number of studies (Al-Habaibeh & Gindy, 2001; Dimla Sr., 2000; Dolinšek & Kopač, 1999; Kuo, 2000; Liang & Dornfeld, 1989; Niu, Wong, Hong, & Liu, 1998; Quan, Zhou, & Luo, 1998; Xiaoli & Zhejun, 1998).

An AE receiver utilizing a Doppler radar motion detector (model MDU 1620: Microwave Solutions, n.d.) has been proposed as another possible technique for TCM systems in a recent study of the advanced sensor technology development (Smith & Lee, 2005). Even though a number of AE transducers, utilizing the piezoelectric effect, are available in the market, only a limited number of sensors can be used while studying the metal cutting process (Dolinšek & Kopač, 1999). The proposed sensor provided an improved installation method since it did not require close setup to workpiece. As a result, it can avoid frictional damage caused by chips formed during the cutting process. The AE sensor was mounted in a plastic case and set up under the workpiece.

Data Acquisition Systems

Additional instruments are necessary to obtain the signals from the sensor and transfer them to a personal computer for signal processing. The sensors generate an analog signal, which must be converted into digital data using an A/D converter along with DaqView data processing software developed by IOTech.

A/D converter

A Daqbook/100 model A/D converter (Omega, n.d.) was employed for this study. It is an external module that can connect to the parallel port of a personal computer for control and data acquisition. It can handle up to 8 signals simultaneously with 12-bit resolution. A screw terminal card (DBK-11) was also employed to receive vibration signals from the 3 directions and the AE signal. This card provided a way to utilize the multi-channel input functions of the A/D converter.

Data acquisition program

DaqView (IOTech, n.d.) a MS-Windows-based software for the A/D converter, was used for control and data acquisition. A proper setup of A/D converter channels, gain, and transducer type was tested before actual data were collected. The stream data were saved to a local disk drive so the data could be used for post-process data analysis and model development. Figure 3.5 shows an example of the setup and data acquisition process of DaqView. The trigger was set to the manual mode so the data acquisition points could be controlled manually. The start position of data collection was set to a half inch after the end of workpiece, and the total data points in each cut were set to 5,000 points (about a half-second duration).

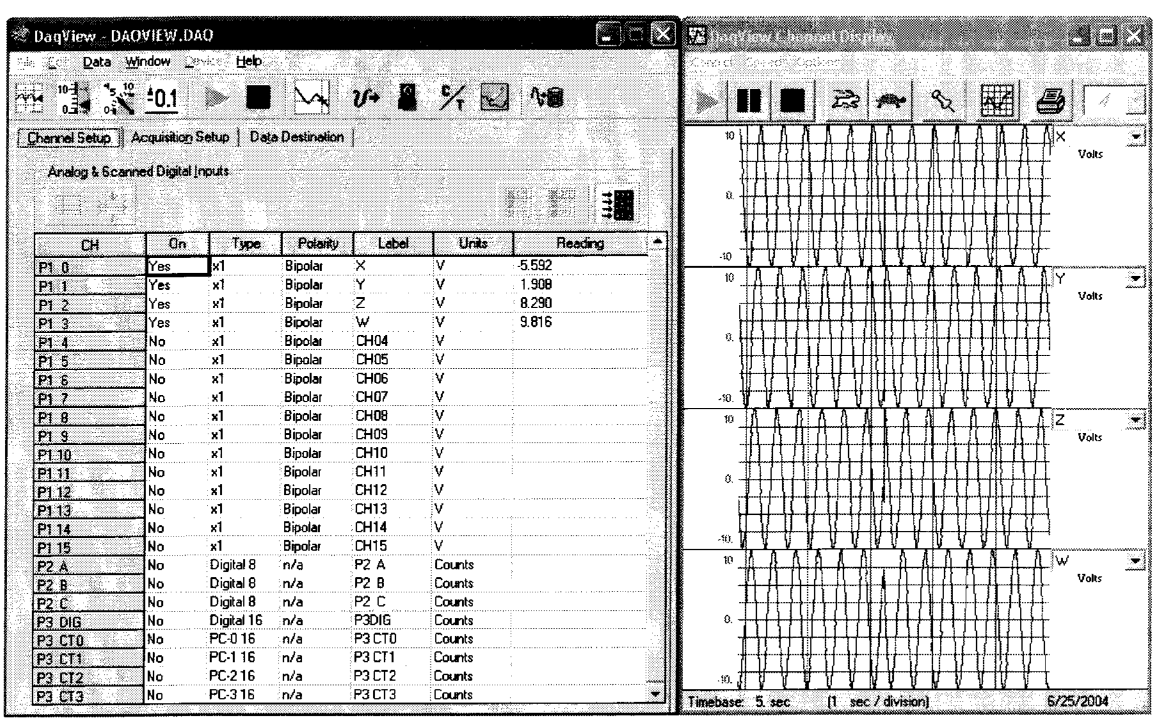


Figure 3.5. Example of DaqView setup and data acquisition process

Summary of Hardware and Software Setup

The tool condition monitoring system developed in this research utilized two sensor technologies and a data-acquisition system. A tri-axial accelerometer and an AE sensor were mounted in a 7.5 HP, spindle-power CNC lathe to detect the release of energy from the tool and workpiece. The signals detected by the accelerometer were amplified by a PCB sensor signal conditioner and transferred to an A/D converter with the signal from the AE sensor. The signals were recorded to computer storage by the DaqView data acquisition program, which was used to analyze the data.

The goal of this study was to develop a tool condition monitoring system using 3 machining parameters (spindle speed, feed rate, and depth of cut) and the signals detected by the 2 sensors. To conduct the experiment, an experimental design was established. A methodology utilizing three machining parameters and cutting tool conditions without any systematic pattern are introduced in the following section.

Experimental Design

Experimental design

A full factorial design was utilized for this experiment. An ANN model was deployed, based on independent variables for a statistical regression analysis and input neurons. The independent variables utilized in this study were: 3 spindle speeds (SP), 3 feed rates (FR), 3 depths of cut (DC), and signals captured during machining (S_i). Three insert tools with different amounts of flank wear were measured under a microscope before the machining. The measured values were used as the dependent variables in the statistical analysis, and as the output neuron in the ANN model.

Flexible data set

To test the flexibility of the models developed by statistical analysis and neural networks, additional sets of machining parameters were provided. These sets included additional values for spindle speed, feed rate, depth of cut, and tool conditions not used in the analysis and model development. After the experimental design, each cutting condition—including cutting conditions from the flexible data set—were randomly reorganized before the machining was performed to eliminate any systemic integration from the cutting conditions.

A training data set was employed for data analysis and to build the model, which incorporated 3 tools, each with a different amount of wear (0.010714", 0.017857", and 0.019643"). Additionally, a testing data set was used to test the flexibility of the models. Each condition in the testing data set had 2 tools with different amounts of wear (0.007143" and 0.014285"). Table 3.3 shows the experimental design of this study and the flexible data set.

Table 3.3. Experimental design and flexible data set

Training Data Set

	SP		**500**			**1,000**			**1,500**	
FR	**DC**	**0.01**	**0.02**	**0.03**	**0.01**	**0.02**	**0.03**	**0.01**	**0.02**	**0.03**
0.01		S_{01}	S_{02}	S_{03}	S_{10}	S_{11}	S_{12}	S_{19}	S_{20}	S_{21}
0.02		S_{04}	S_{05}	S_{06}	S_{13}	S_{14}	S_{15}	S_{22}	S_{23}	S_{24}
0.03		S_{07}	S_{08}	S_{09}	S_{16}	S_{17}	S_{18}	S_{25}	S_{26}	S_{27}

SP: Spindle Speed (rpm)
FR: Feed Rate (inch/min)
DC: Depth of Cut (inch)
S_i: Specimen

Table 3.3. Experimental design and flexible data set (continued)

Flexible Data Set

	SP	625		825	
FR	**DC**	**0.015**	**0.025**	**0.015**	**0.025**
0.015		S_{28}	S_{29}	S_{32}	S_{33}
0.025		S_{30}	S_{31}	S_{34}	S_{35}

CHAPTER 4. DATA ANALYSIS AND STATISTICAL MODEL

To develop the TCM system, it was necessary to obtain three data sets from each machining condition, with three different tool conditions. To test the flexibility of this system, another data set from each additional machining condition with three tool conditions was also obtained. Given this data, this chapter introduces the statistical properties of the raw signal, the methodology of decomposing the raw signal to find significant components, and the development of a statistical model utilizing the decomposed raw signals.

Decomposition of Raw Signals

In order to utilize the raw signals obtained from the sensor, the statistical characteristics of the signals of each machining condition were tested, and the most significant signal components from the raw signal were obtained. This section explains the procedures for these activities.

Statistical properties of the raw signals

A total of 270 data sets containing raw signals were obtained from the experiment. Data analysis and modeling required a methodology to discern particular signal characteristics from the raw data. Many such analysis methods have been suggested in past research, including time-domain analysis and frequency-domain analysis. Since the raw data obtained from the experiments included unwanted outside noise, the frequency-domain analysis alone was insufficient to distinguish between the specific amplitude fluctuations that arose from changes in the machining parameters being studied.

The traditional time-domain analysis does not provide a clear method to analyze raw signal data in this case, due to the unpredictability (or randomness) of each data points. A better way is to statistically analyze the properties of each data set and to use these statistics to map data to changes in tool conditions. Among the many statistical properties of raw signals (such as mean value, maximum value, minimum value, standard deviation, etc.), several studies have suggested that the adjusted mean value or root mean square (RMS) of the signal data can be used to represent the characteristics of the raw signal (Abu-Mahfouz, 2003; Amick, H. (1998); Liang, Kwon & Chiou, 2004; Bonifacio & Diniz, 1994). Based on these findings, this study utilized the adjusted mean values of each member in the data set to define the overall characteristics of the data from the experiment. Appendix B shows the machining parameters and signal properties obtained in the experiment.

Signal decomposition

The raw signal obtained from the sensors contains not only the signal generated from the interactions of the tool and workpiece, but also background "noise" signals from other sources, such as the hydraulic pump motor, feed motors, and environmental vibrations. Therefore, it is almost impossible to detect or obtain any desired characteristic free of all the others. There is also no guarantee that detecting only the desired signals is an effective means of monitoring the tool condition.

Several studies have employed a signal decomposition technique for TCM systems (Tansel et al., 1995; Xiaoli & Zhejun, 1998; Wu & Du, 1996; Klocke, Reuber & Kratz, 2000; Wang, Mehrabi, & Kannatey-Asibu Jr., n.d.). However, these studies utilized only the noise-cancellation aspect of the wavelet transform. Using this method, there is also no guarantee that the filtered signals, obtained after canceling the signals categorized as noise, is sufficient for monitoring the tool condition. Therefore, it is necessary to analyze each signal component obtained by the signal decomposition process in order to find those most suitable to the task of detecting the tool condition.

This study employed Matlab and its add-on wavelet toolbox to decompose the signal. Appendix C shows the Matlab program developed for the decomposition process, and Figure 4.1 shows an example of the decomposition process in Matlab. Four types of signals (vibrations from the x-, y-, and z-directions, as well as acoustic emission [AE] signals) were employed in this study. Data from each raw signal were transferred to Matlab and decomposed into six components. For the decomposition process, the 4-level Daubechies decomposition scheme was employed. After the decomposition, the adjusted mean value of each component was stored for further data analysis. The next section describes the statistical analysis to find the most significant signal component.

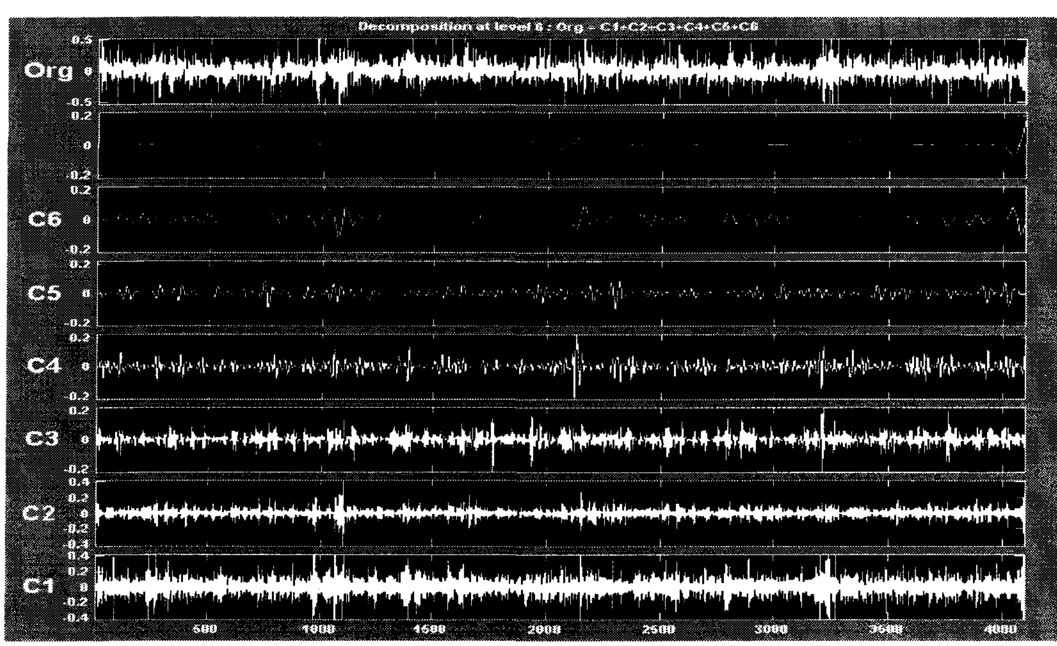


Figure 4.1. Example of signal components decomposed by wavelet transform

Test the significance of the signal components

Decomposing the raw data obtained six component signals from each of the raw signal data. The adjusted mean value of each signal component was calculated and utilized as the statistical character of each component. In order to find the most significant component to detect tool conditions, a statistical analysis was performed. Using a multivariate test in JMP, each signal component was correlated to tool wear amounts. Table 4.1 shows the correlation factors between the tool wear amount and raw signal data and its components of vibration from the x-, y-, and z-directions as well as AE signals.

The test revealed that component 6 of the x-, y-, and z-direction vibration signals had the most significant relationship to tool wear. Compared with the original signals, dramatic increases of correlations with tool wear amount were found. However, results from the AE signal analysis show that the original signals have a more significant relationship to tool wear amount than its decomposed components. From the test results, component 6 of each vibration signal and AE signals was employed to represent each of the signals for further statistical analysis.

Table 4.1. Correlation factors of tool wear and signal components of four signals

Signal	Org	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6
X	.041570	.000708	.036834	.079329	.266055	.241379	.536925
Y	.095862	.013675	.026677	.028840	.072718	.075334	.361890
Z	.003057	.019938	.043196	.057798	.192967	.200215	.513471
W	.121421	.087464	.086403	.059550	.079244	.030679	.042767

X: x-direction vibration, Y: y-direction vibration, Z: z-direction vibration, W: AE signals
Org: original signal, Comp1 – 6: signal components

Test Multicollinearity of the Parameters

To further test this data, this study employed a multiple regression analysis. The independent variables in this analysis were: different machining conditions; the combinations of spindle speed, feed rate, and depth of cut; and the signals obtained from two sensors. The dependent variable was the amount of tool wear under each cutting condition. However, high interactions are to be expected between the machining parameters and signals employed as independent variables. This crossed relationship among independent variables is called multicollinearity. The existence of multicollinearity can be interpreted as the duplicated effects of some independent variables to the other independent variables. All of the independent variables are used to predict the dependent variables. The following sections introduce the method to test multicollinearity among the independent variables, machining parameters, and signals. Additionally, these sections describe the method to eliminate the effect of variables of machining parameters from variables of signals.

Multivariate test and correlations of parameters

In order to find the existence of the duplicated effects of independent variables on dependent variables, a multivariate test was performed. The Pearson correlation factors of each of the variables were calculated based on the following equation.

$$r = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2}\sqrt{\sum (y-\bar{y})^2}} \tag{4.1}$$

where r = Pearson correlation factor of two variables x and y

$\bar{x}, \bar{y}$ = mean of variables x and y

Table 4.2 summarizes the test results showing the significant relationships between spindle speed, three vibration signals, and the AE signals. The following Pearson correlation factors were found: 0.1290 between the spindle speed and x-direction vibrations; 0.4066 between spindle speed and y-direction vibrations; 0.2663 between spindle speed and z-direction vibration; and 0.2847 between spindle speed and AE signals. A significant relationship between feed rate and AE signals was also found.

Table 4.2. Pearson correlation factors of the independent variables

	V_x	V_y	V_z	W
S	-.1290*	-.4066*	-.2663*	-.2847*
F	-.0179	-.0974	-.0776	-.4340*
D	.0144	.0358	.0167	-.0725

* Correlation is significant at the 0.05 level (two-tailed)
S: Spindle speed, F: Feed rate, D: Depth of cut
V_x: x-direction vibration, V_y: y-direction vibration, V_z: z-direction vibration, W: AE signals

Table 4.3 summarizes the relationships between the interaction terms of the machining parameters and signals. The data in Tables 4.2 and 4.3 was used to find significant relationships between machining parameters and the signals from the two sensors. These test results show that the multiple regression model cannot be accurately developed until the machining parameter data can be eliminated from the signal data (which are also employed as the independent variables). The following section briefly introduces the methodology to eliminate the effects of the machining parameters from the vibration and AE signal variables.

Table 4.3. Relationships of the interaction terms of machining parameters with the signals

	V_x	V_y	V_z	W
S×F	-.0648	-.3102	-.1932	-.4570
S×D	-.0938	-.3074	-.2016	-.3515
F×D	-.0387	-.0540	-.0636	-.2994
S×F×D	-.0803	-.2729	-.1811	-.4279

S: Spindle speed, F: Feed rate, D: Depth of cut
V_x: x-direction vibration, V_y: y-direction vibration, V_z: z-direction vibration, W: AE signals

Elimination of the effect of machining parameters

The multivariate test showed the existence of multicollinearity among independent variables. In order to minimize duplicated effects of the independent variables from the dependent variable, a statistical technique utilizing multiple regression analysis was employed.

In order to eliminate the effects of machining parameters from the vibration signals of three directions and AE signals, the following assumption was applied:

$$S_i = f_i(SP_i, FR_i, DC_i) + E_i + e_i \tag{4.2}$$

where S_i = measured signals from a sensor

SP_i = spindle speed

FR_i = feed rate

DC_i = depth of cut

E_i = effect of signals

e_i = error

This assumption allows a multiple regression analysis with interaction terms to be used to eliminate the effect of the spindle speed, feed rate, and depth of cut from the raw signals. In the analysis, each signal was tested as an independent variable and the machining parameters were employed as the dependent variables. By subtracting the predicted values of each signal from the observed values and the machining parameters, a new signal value was obtained. Finally, the new signal values can be assumed not to have the effects of machining conditions, spindle speed, feed rate, and depth of cut. Table 4.4, Table 4.5, Table 4.6, and Table 4.7 show the results of a statistical test of each signal.

Table 4.4. ANOVA and parameter estimates of the x-direction vibration signals

Summary of Fit

R Square	Adjusted R Square	Root Mean Square Error	Mean of Response
.05539	.02725	.010626	.019797

Analysis of Variance

Source	df	Sum of Square	Mean Square	F	Sig.
Model	7	.00155586	.000222	1.9685	.0602
Error	235	.02653343	.000113		
C. Total	242	.02808929			

Parameter Estimates

Term	Estimate	Std Error	T	Sig
Intercept	.012547	.012624	.99	.3248
S	-.000001	.000012	-.09	.9308
F	.3321411	.584391	.57	.5703
D	.9671704	.584391	1.66	.0993
S×F	.0000667	.000541	.12	.9020
S×D	-.000526	.0000541	-.97	.3322
F×D	-38.12174	27.05203	-1.41	.1601
S×F×D	.0170011	.025045	.68	.4979

Table 4.5. ANOVA and parameter estimates of the y-direction vibration signals

Summary of Fit

R Square	Adjusted R Square	Root Mean Square Error	Mean of Response
.23915	.216487	.012945	.029264

Analysis of Variance

Source	df	Sum of Square	Mean Square	F	Sig.
Model	7	.01237747	.001768	10.5522	.0001
Error	235	.03937857	.000168		
C. Total	242	.05175604			

Parameter Estimates

Term	Estimate	Std Error	T	Sig
Intercept	.0197943	.015379	1.29	.1993
S	.0000072	.000014	-.50	.6159
F	.2256959	.711929	.32	.7515
D	1.8819465	.711929	2.64	.0088
S×F	-.000179	.000659	-.27	.7866
S×D	-.001592	.000659	-2.42	.0165
F×D	-45.37295	32.9559	-1.38	.1699
S×F×D	.0343189	.030511	1.12	.2618

Table 4.6. ANOVA and parameter estimates of the z-direction vibration signals

Summary of Fit

R Square	Adjusted R Square	Root Mean Square Error	Mean of Response
.120281	.094076	.010712	.02219

Analysis of Variance

Source	df	Sum of Square	Mean Square	F	Sig.
Model	7	.00368694	.000527	4.5901	.0001
Error	235	.02696585	.000115		
C. Total	242	.03065279			

Parameter Estimates

Term	Estimate	Std Error	T	Sig
Intercept	.0203332	.012727	1.60	.1115
S	-.000002	.000012	-.16	.8737
F	.0471871	.589133	.08	.9362
D	1.0568589	.589133	1.79	.0741
S×F	.0001165	.000545	.21	.8311
S×D	-.000764	.000545	-1.40	.1629
F×D	-32.24364	27.27158	-1.18	.2383
S×F×D	.018725	.025249	.74	.4591

Table 4.7. ANOVA and parameter estimates of the AE signals

Summary of Fit

R Square	Adjusted R Square	Root Mean Square Error	Mean of Response
.513615	.499127	.124388	.394607

Analysis of Variance

Source	df	Sum of Square	Mean Square	F	Sig.
Model	7	3.8395492	.548507	35.4509	.0001
Error	235	3.6359913	.015472		
C. Total	242	7.4755405			

Parameter Estimates

Term	Estimate	Std Error	T	Sig
Intercept	.055719	.147782	.38	.7065
S	.0007262	.000137	5.31	.0001
F	3.9698506	6.840957	.58	.5623
D	38.315946	6.840957	5.60	.0001
S×F	-.021779	.006334	-3.44	.0007
S×D	-.04836	.006334	-7.64	.0001
F×D	-961.2863	316.6756	-3.04	.0027
S×F×D	1.3856094	.293185	4.73	.0001

From the test results in Table 4.4, Table 4.5, Table 4.6, and Table 4.7, four prediction models for each signal were developed. Each model employed spindle speed (S), feed rate (F), and depth of cut (D) as independent variables. Hence, each predicted signal ($\hat{V}_X$: predicted x-direction vibrations; $\hat{V}_Y$: predicted y-direction vibrations; $\hat{V}_Z$: predicted z-direction vibrations; $\hat{V}_W$: predicted AE signals) was described as follows:

$$\begin{aligned}\hat{V}_{Xi} &= .012547 - .000001\,S_i + .332111\,F_i + .9671704\,D_i + .0000667\,S_iF_i \\ &- .000526\,S_iD_i - 38.12174\,F_iD_i + .0170011\,S_iF_iD_i\end{aligned} \tag{4.3a}$$

$$\begin{aligned}\hat{V}_{Yi} &= .0197943 - .0000072\,S_i + .2256959\,F_i + 1.8819465\,D_i - .000179\,S_iF_i \\ &- .001592\,S_iD_i - 45.37295\,F_iD_i + .0343189\,S_iF_iD_i\end{aligned} \tag{4.3b}$$

$$\begin{aligned}\hat{V}_{Zi} &= .0203332 - .000002\,S_i + .0471871\,F_i + 1.0568589\,D_i + .0001165\,S_iF_i \\ &- .000764\,S_iD_i - 32.24364\,F_iD_i + .018725\,S_iF_iD_i\end{aligned} \tag{4.3c}$$

$$\begin{aligned}\hat{V}_{Wi} &= .055719 + .0007262\,S_i + 3.9698506\,F_i + 38.315946\,D_i - .021779\,S_iF_i \\ &- .04836\,S_iD_i - 961.2863\,F_iD_i + 1.3856094\,S_iF_iD_i\end{aligned} \tag{4.3d}$$

Therefore, the vibration signals (V_X, V_Y, and V_Z) and the AE signal (V_W) were transformed by the following equations.

$$\begin{aligned}V'_{Xi} &= V_{Xi} - \hat{V}_{Xi} = V_{Xi} - .012547 + .000001\,S_i - .332111\,F_i - .9671704\,D_i \\ &- .0000667\,S_iF_i + .000526\,S_iD_i + 38.12174\,F_iD_i - .0170011\,S_iF_iD_i\end{aligned} \tag{4.4a}$$

$$\begin{aligned}V'_{Yi} &= V_{Yi} - \hat{V}_{Yi} = V_{Yi} - .0197943 + .0000072\,S_i - .2256959\,F_i - 1.8819465\,D_i \\ &+ .000179\,S_iF_i + .001592\,S_iD_i + 45.37295\,F_iD_i - .0343189\,S_iF_iD_i\end{aligned} \tag{4.4b}$$

$$\begin{aligned}V'_{Zi} &= V_{Zi} - \hat{V}_{Zi} = V_{Zi} - .020332 + .000002\,S_i - .0471871\,F_i - 1.0568589\,D_i \\ &- .0001165\,S_iF_i + .000764\,S_iD_i + 32.24364\,F_iD_i - .018725\,S_iF_iD_i\end{aligned} \tag{4.4c}$$

$$\begin{aligned}V'_{Wi} &= V_{Wi} - \hat{V}_{Wi} = V_{Wi} - .055719 - .0007262\,S_i - 3.9698506\,F_i - 38.315946\,D_i \\ &+ .021779\,S_iF_i + .04836\,S_iD_i + 961.2863\,F_iD_i - 1.3856094\,S_iF_iD_i\end{aligned} \tag{4.4d}$$

Finally, three direction vibration signals and the AE signal could be considered as independent variables to carry out a multiple regression analysis of the dependent variable, the tool wear amount. Appendix D shows the transformed vibration and AE signals that were used to develop a multiple regression model to predict the tool wear amount.

Multiple Regression Analysis

By utilizing the decomposed and transformed vibration and AE signals from equation 4.4, a statistical data analysis was performed to develop a model to predict the tool condition. Through the decomposition process and a simple statistical data analysis, the most significant signal components of the vibration signals of each direction and the AE signal were obtained. In order to utilize the obtained signals in a statistical model, multicollinearity among the independent variables was tested. From a simple statistical technique, the effects of the machining parameters (spindle speed, feed rate, and depth of cut) were eliminated from the signal data. From the decomposition and transformation process, a new adjusted mean value (the arithmetic mean of the values of the departure of each signal point from its mean value), was obtained and employed to develop the statistical model. In order to test the benefit of the decomposition process, two statistical models were developed. One model employed significant signal components obtained from the decomposition process, and the other model employed raw signals obtained from the sensor. The following section explains and compares the properties of the two models.

In this study, statistical multiple regression models with interactions among the independent variables were developed. As shown in Table 4.8.1 and Table 4.8.2, the R^2 value of the model that employed the raw signal data without a decomposition process was 0.733, which indicates that 73.3 % of the observed variability of the tool wear amount can be explained by the independent variables. Since a full factorial analysis was performed, 128 (2^7) terms for the multiple regression models were obtained from the seven independent variables. The estimated coefficient values of each term are shown in Appendix E.

In the same manner, another model was developed, employing the significant components of the vibration and AE signal from the decomposition process. The statistical test results are shown in Table 4.9.1 and Table 4.9.2. According to the test, the R^2 value of the model was 0.818, which indicates that the 81.8 % of the observed variability of the tool wear amount was explained by the independent variables. Since the model also employed full factorial analysis, it has 128 (2^7) terms from the seven variables. The coefficient values of each term are shown in Appendix F. From the comparison of its R^2 values, the model with a signal decomposition process showed 12.6% improved prediction performance over the model without the signal decomposition process.

Statistical test were performed to further test the significance of the improvement of Model B, which employed the significant signal components from the decomposition process, versus Model A, which employed raw signals. The following hypothesis was tested:

$$H_0: \phi_{Model\ A} = \phi_{Model\ B}$$

$$H_1: \phi_{Model\ A} \neq \phi_{Model\ B}$$

where $\phi_{Model\ A}$ = deviation of Model A in the data set, and $\phi_{Model\ B}$ = deviation of Model B in the data set.

Table 4.8.1. Summary of the model with raw signal data

R^2	Adjusted R^2	Observations	Root Mean Square Error	Mean of Response
.733	.439	243	.002895	.016071

Table 4.8.2. Analysis of Variance of the model with raw signal data

Source	Df	Sum of Squares	Mean Square	F	Sig.
Model	121	.00265198	.000021	2.4909	<.0001
Error	115	.00096408	.000008		
C. Total	242	.00361607			

Table 4.9.1. Summary of the model with significant signal component data

R^2	Adjusted R^2	Observations	Root Mean Square Error	Mean of Response
.818	.617	243	.002391	.016071

Table 4.9.2. Analysis of Variance of the model with significant signal component data

Source	Df	Sum of Squares	Mean Square	F	Sig.
Model	121	.00295844	.000023	4.0735	<.0001
Error	115	.00065763	.000006		
C. Total	242	.00361607			

From the test results shown in Tables 4.10.1 and 4.10.2, the hypothesis was rejected, which means that the mean deviation values of Model B were significantly smaller than the mean deviation value of Model A. These test results proved that there is a significant benefit of adopting a signal decomposition process in the development of multiple regression model for the TCM system.

Table 4.10.1. Comparison of Model A and Model B

	N	Mean	Standard Deviation	Standard Error Mean
Deviation of Model A	243	.0015517	.0012514	.0000803
Deviation of Model B	243	.0011655	.0011131	.0000714

Table 4.10.2. Test results of Model A and Model B

Levene's Test for Equality of Variance		T-Test for Equality of Means				
F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
5.275	.022	3.595	484	.000	.0001383	.0000089

The developed model was tested by a new set of data. The test included 151 data with various tool wear amounts and independent variable values. The prediction capability of the developed model was tested based on the criterion of detecting the rejecting tool condition, (STOP-GO), which provides a practical applicability in actual manufacturing situations (Dimla Jr., Lister & Leighton, 1998; Dimla Sr. & Lister, 2000b). The amount of tool wear to reject was set to 0.00787" (0.2 mm) or bigger. This threshold represents the maximum practical amount of flank wear in a turning operation for precision machining. This threshold for flank wear is smaller than the value suggested by ISO 3685 (0.3 mm) for general machining (Dimla Jr., Lister & Leighton, 1998; Kopač & Šali, 2001; Pavel, Sinram, Combs, Deis & Marinescu, 2002). Appendix G shows the results of each data test.

Table 4.11 shows the results of the statistical regression model with 151 tests, including 62 sharp tools and 89 worn tools based on the criterion of a flank wear size larger than 0.2 mm (0.007987 inch). From the 62 sharp tool tests, 10 samples were predicted as a worn tool (type II error). The model showed 84% accuracy to sense sharp tools. From the 89 worn tool tests, 5 samples were predicted as sharp tool (type I error). The model showed 94% accuracy to sense worn tools. Overall the developed multiple regression model that adopted a signal decomposition process showed 90% accuracy to identify the tool condition based on the criterion of 0.2 mm flank wear size.

Table 4.11. Summary of test result

		Predicted		
		Sharp Tool	Worn Tool	Total
Observed	Sharp Tool	**52**	10	62
	Worn Tool	5	**84**	89
	Total	57	94	151

Number of sharp tool samples predicted accurately: 52 out of 62 (84% accuracy)
Number of worn tool samples predicted accurately: 84 our of 89 (94% accuracy)
Total number of tool samples predicted accurately: 136 out of 151 (90% accuracy)

Summary

This chapter presented statistical data analyses of experimental results. A wavelet signal decomposition technique was performed to find the most significant signal component to predict the tool condition with four different signals (three direction vibration signals and AE signals) detected during turning operations. The wavelet signal decomposition technique improved by 12.6% the model's capability to explain tool wear from the machining parameters and four types of sensor signals. In this study, a simple statistical technique was also adopted to eliminate the effects of machining parameters from the four signals before a final statistical model was developed. Figure 4.2 shows the operation of the statistical model. For practical use in a manufacturing environment, the developed model was tested as a tool to detect "STOP-GO", and comparing the current tool condition with the preset amount of flank tool wear for continuous machining. The model predicted tool conditions with 91% accuracy from 151 test samples.

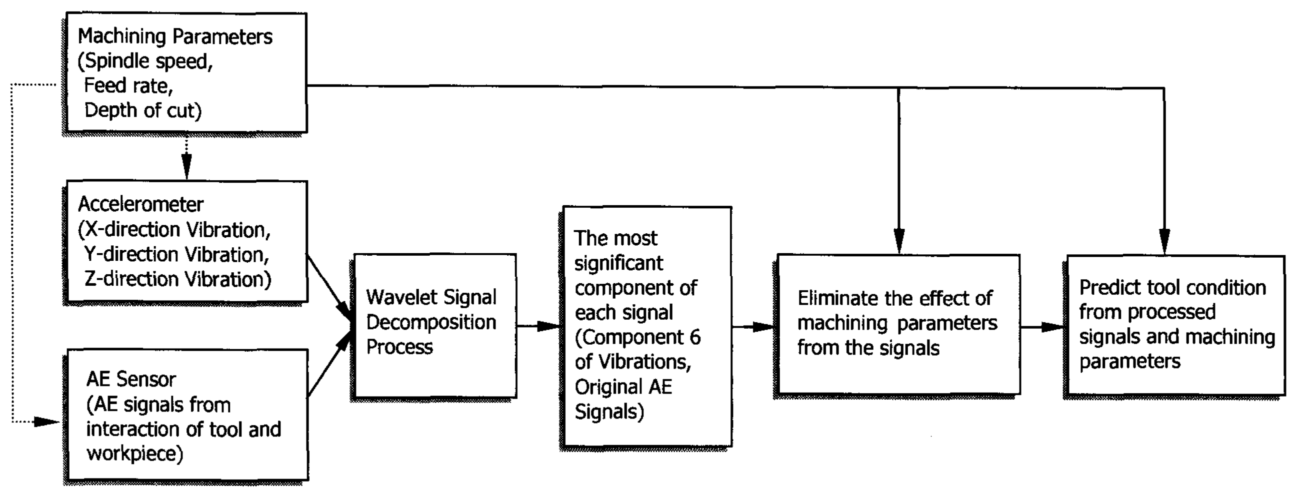


Figure 4.2. The process of statistical model operation for tool condition

CHAPTER 5. ARTIFICIAL NEURAL NETWORKS MODEL

Although the statistical regression model developed in the previous chapter showed a high accuracy of tool condition monitoring in turning operations, the nonlinear relationships among the variables could be explained further with a different approach. Among a number of methods, artificial neural networks (ANNs) are well-known for their capability to solve nonlinear problems. Therefore, ANNs could be expected to improve a tool condition monitoring system.

Artificial neural networks provide an artificial means of making some of the same kinds of decisions that a highly skilled machine operator would make before, during, or after the machining process (Masory, 1991). Human operators, like ANNs, learn to make accurate judgments of tool conditions based on relationships observed during the machining process. As human operators gain experience, their sensitivity to these relationships increases. More recent experience reinforces or adjusts the patterns developed from prior experience. ANNs work in a similar fashion, continually training their ability to accurately judge tool conditions. By adjusting the weights among neural networks nodes until the number of test errors falls to an acceptable level, the nonlinear relationships among the factors and tool condition are updated and tested. The following sections will explain the methods of developing ANNs for a tool condition monitoring system.

This chapter is divided in two sections: the procedure for developing an Artificial Neural Networks-based Tool Condition Monitoring System (ANN-TCMS), followed by the test results of the developed system. The first section presents the data examination and pre-process, search and evaluation of ANN structures, and training results. The second section presents the performance of the developed system and compares it to the statistical model presented in the previous chapter.

Determining the Network Structure for the ANN-TCMS

Determining the network structure (the number of hidden layers and nodes of each layer) that performs best is one of the biggest challenges in the process of developing ANNs. The structure of the system is determined by the amount of data available for the training procedure, as well as the characteristics of the data (including statistical relationships and distribution). Many machining tool studies utilizing ANNs have assumed only a limited number of cases or searched by trial-and-error in order to determine the appropriate structure (Dimla Jr., Lister & Leighton, 1998; Chen & Chen, 2002; Venkatesh, Zhou & Caudill, 1997). Investigating a limited number of cases of the ANN structure could lead the investigation to unexpected results, such as outranged errors. As a result, there is often a low probability of obtaining the best-performing system with the available data.

Alternatively, in a trial-and-error methodology, the researcher has to spend a great amount of time to modify the ANNs structure, as well as the numbers of hidden layers and neurons. Additionally, the researcher must train the systems until the test results are valid. They also must decide upon the proper learning rate and momentum value, if a back-propagation learning algorithm is used. As a result, this method requires a great deal of time to optimize the network training time and output results (Dimla Sr. 1999).

A novel methodology to find the optimized ANNs structure for tool condition monitoring is proposed in this study. In order to overcome the problems of the traditional manual method (inefficient, time consuming, and inaccurate) to determine the ANNs structure, a computer-assisted methodology was used. The manual method tests the structure of the ANNs with full training iterations (repeated adjusting of weights of each node) in each time, which causes great amount of time and potential of inaccuracies during the ANNs structure modification. However, the computer-assisted method used in this research tests all possible structures with a simplified learning process and training iteration, providing a fitness score for each structure. This fitness score allows the researcher to focus on a limited number of structures having higher scores. The detailed procedure for the computer-assisted method to test ANNs structure will be discussed after the data pre-processing section.

For the input layer of ANN-TCMS, three machining conditions (spindle speed, feed rate, and depth of cut), three accelerometer signals (vibration from the x-, y-, and z-direction), and AE (acoustic emission) sensor signals were adopted. The output layer has one node (the amount of flank wear of the tool used in each experiment). For the accelerometer and AE signals, the best components of each signal (determined by the wavelet transformation and statistical tests in the previous chapter) were utilized since they exhibited a closer relationship with tool conditions than raw signals. However, the procedure for eliminating the effects of machining conditions from the accelerometer signals and AE signal was not performed since the nonlinear relationships among the input layer nodes (three machining conditions, three accelerometer signals, and AE signal) are transformed into the weights among the nodes of the ANN during the training procedure. Therefore, three spindle speeds, three feed rates, three depths of cut, and five different tool conditions were adopted in this study. For the accelerometer signals, as discussed in the previous chapter, component six of each direction of vibration and AE signal was used. The original data of the AE signal were also used as the input nodes.

In order to utilize the data in ANNs training, a preprocessing of the data is required to give equal initial weights into the input layer. All input layer node data (machining conditions and sensor signals) were transformed into the range between -1. and 1. (normalization), and the output node (the amount of flank wear) was transformed into the range of between 0. and 1. The new dataset obtained after preprocessing is shown in Appendix H.

After preprocessing, the best-performing ANNs structure was determined using a computer-assisted method. This methodology verifies the performance of all possible structures automatically based on the criteria of interest to the researcher. In this study, the number of the hidden layers was limited to one and two (both cases were tested), and the number of nodes per hidden layer was limited to thirty, due to the limitations in available computing power. Therefore the number of possible structures for the ANNs system is 930. Each of these possible structures was tested and scored based on its fitness to the tool conditions. During the test, a simplified learning algorithm (Quick-propagation) was utilized to shorten the learning time with a limited number of iterations.

Quick-propagation is a heuristic modification of the back-propagation algorithm invented by Fahlman (1988) to simplify the training process by providing variable momentum factors. It has been proven to be much faster than general back-propagation learning in many problems, despite a risk of instability and a tendency to stay in local solutions during the learning process (Eggermont, 1998). The only coefficient value required during the learning procedure is the learning magnitude value. This value controls the speed by which this method searches between the different structures. The simplicity of this learning algorithm allowed the researcher to investigate the network structures more quickly than through the use of a back-propagation learning algorithm.

Included in the test results of 930 ANNs structures were fitness scores based on criteria of interest to the researcher. In this study, the inverse test error of each structure with the designated training iteration (2500) was used to verify the performance of each structure. Table 5.1 shows the test results of the top 35 systems with the number of weights, the connections between nodes of the next layers, its fitness score, inverse test error, and training error. The test results show that the number of weights is not related to the fitness of the system. However, it is clear that multiple hidden layers show a better fitness to the examined data compared to a single hidden layer system. An irregular relationship between the degree of fitness and the structure of ANNs systems (the number of nodes in each hidden layers) was also observed. From the test results, the top 22 structures (all with a fitness score of 400 or more), were evaluated to determine the best fit for the tool condition monitoring system.

Training the ANNs System

A new series of neural-networks training was performed with these 22 network structures. A total of 405 data sets were used as training data, including three different spindle speeds, feed rates, and depths of cut with five different tool conditions. Each combination of spindle speed, feed rate, depth of cut, and tool condition has three sets of data. A back-propagation learning algorithm was used for the network learning algorithm . This method is known to have a slower learning speed but fairly accurate learning results. Learning rates and momentum values for each neural-networks were arranged by the negotiation of the speed of convergence and the prevention of divergence during the training.

Table 5.1. Summary of the top 34 networks systems after structure search

ID	Architecture*	Number of weight	Fitness score	Inverse test error	Train error
236	7-14-8-1	409	448.703444	0.002229	0.003321
195	7-29-6-1	767	431.531508	0.002317	0.002982
101	7-19-3-1	444	427.816747	0.002337	0.003125
738	7-12-26-1	605	425.111223	0.002352	0.003446
598	7-12-21-1	535	425.080106	0.002352	0.003281
852	7-14-30-1	761	423.547217	0.002361	0.003237
242	7-20-8-1	577	422.291485	0.002368	0.003369
327	7-21-11-1	674	421.018051	0.002375	0.003256
851	7-13-30-1	711	418.271546	0.002391	0.003387
351	7-17-12-1	569	411.719799	0.002429	0.003428
138	7-28-4-1	681	411.177160	0.002432	0.003003
272	7-22-9-1	657	410.725640	0.002435	0.003480
739	7-13-26-1	651	405.973689	0.002463	0.003597
239	7-17-8-1	493	404.659469	0.002471	0.003181
111	7-29-3-1	674	404.409089	0.002473	0.003454
189	7-23-6-1	611	402.797041	0.002483	0.003681
269	7-19-9-1	570	401.746901	0.002489	0.003762
150	7-12-5-1	311	401.460845	0.002491	0.003479
271	7-21-9-1	628	401.443044	0.002491	0.003261
245	7-23-8-1	661	401.366359	0.002491	0.003185
580	7-22-20-1	921	401.267746	0.002492	0.003457
267	7-17-9-1	512	401.249401	0.002492	0.003419
737	7-11-26-1	559	399.767005	0.002501	0.003660
222	7-28-7-1	771	396.488573	0.002522	0.003405
436	7-18-15-1	661	396.432191	0.002522	0.003367
93	7-11-3-1	260	395.568345	0.002528	0.003196
251	7-29-8-1	829	395.425971	0.002529	0.003434
692	7-22-24-1	1017	394.911352	0.002532	0.003491
829	7-19-29-1	990	394.889463	0.002532	0.003397
214	7-20-7-1	555	394.358644	0.002536	0.003241
196	7-30-6-1	793	394.276727	0.002536	0.003477
216	7-22-7-1	609	392.866558	0.002545	0.003463
207	7-13-7-1	366	391.386744	0.002555	0.003464
712	7-14-25-1	681	391.355128	0.002555	0.003422

* Input Layer – Hidden Layer 1 – Hidden Layer 2 – Output Layer

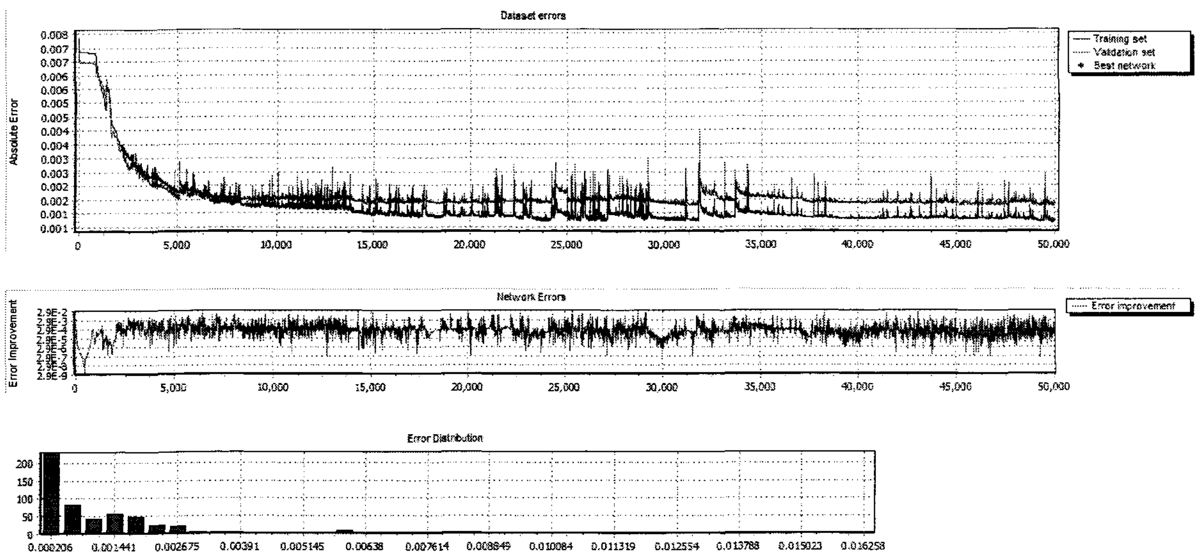
The iteration number for training was set at 50,000 and each structure was trained four times. This setup helped to ensure that the learning results avoid a local solution, which is a false response of neural-networks during the process of node weights adjustment in the training.

During the training iterations, the convergence of the system was checked by monitoring the system training error, error improvement, and error distribution. Figures 5.1.1through 5.1.22 show the results of training the top 22 networks systems. The results show the successful convergence of the all 22 networks systems with high R-squared scores, the range between 0.831101 (networks ID: 150) and 0.996173 (networks ID: 245), which indicated that the tool conditions used in training procedures can be explained by the input variables up to 99.61%. However, the result could be from the learning characteristic of neural networks and does not always indicate the prediction capability of the network structures. Therefore, the prediction capability of the networks structures was tested with the same test data set used in the previous chapter. To summarize the tests shown in Table 5.2, the 22 network systems were able to explain the test data set with an accuracy range between 73.65% (network 150) and 87.78% (network 245). Because of its relatively higher accuracy, network 245 (7-23-8-1) was nominated as the model for the ANN-TCM system in this study.

With the selected network structure, a test was performed based on the criterion of detecting the rejecting tool condition (0.00787" [0.2 mm] or bigger), which could practically be adopted as a "STOP-GO" tool in the real manufacturing. The test result is shown in Appendix I. As shown in Table 5.3, the networks system successfully predicted 146 tests out of a total of 151. From the 62 "sharp tool" tests, five samples were predicted as a "worn tool" (five Type II errors). Within the 89 "worn tool" tests, zero samples were predicted as a "sharp tool" (zero Type I errors). Overall the developed neural networks prediction model can identify the tool condition with 97% accuracy.

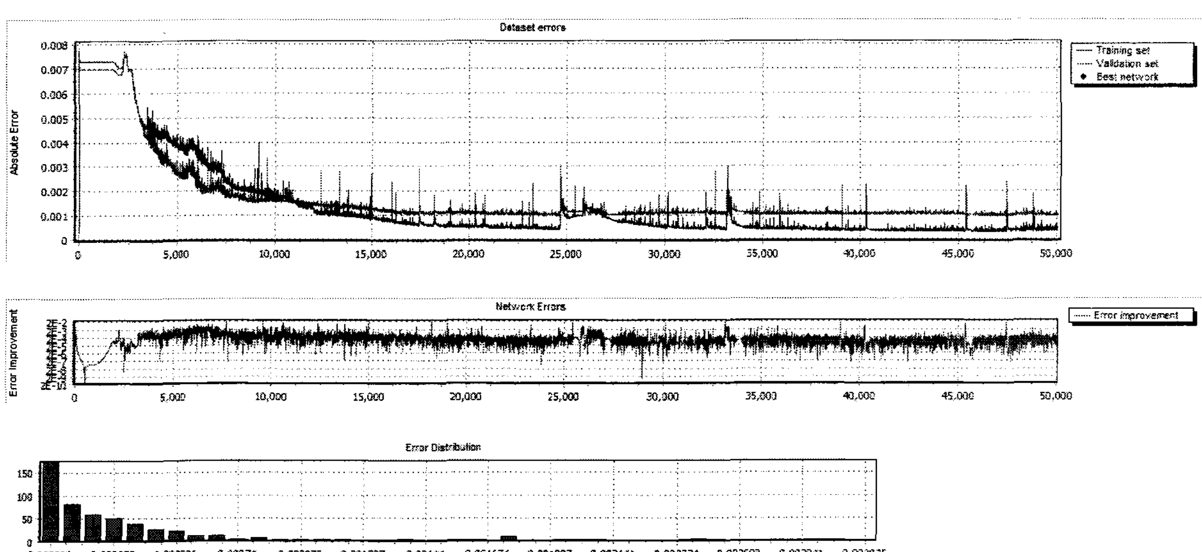
Summary

In this chapter, an Artificial Neural Networks-based Tool Condition Monitoring System (ANN-TCMS) was presented. Three machining factors (spindle speed, feed rate, and depth of cut) and signals detected by a tri-axial accelerometer and an AE sensor were successfully adopted to develop the ANN-TCMS. The most significant signal components, generated by Wavelet transformation, were adopted as the signal inputs. Therefore, seven inputs (three machining factors, three types of accelerometer signals, and AE signals) were utilized to predict one output (tool condition). Figure 5.2 shows the process of the neural networks model operation. An efficient approach to find the best ANN structure from 930 possible structures was also presented. A back-propagation learning algorithm was adopted to develop the networks system. The test results showed 97% accuracy to detect the 151 samples when it is adopted as a "STOP-GO" tool.



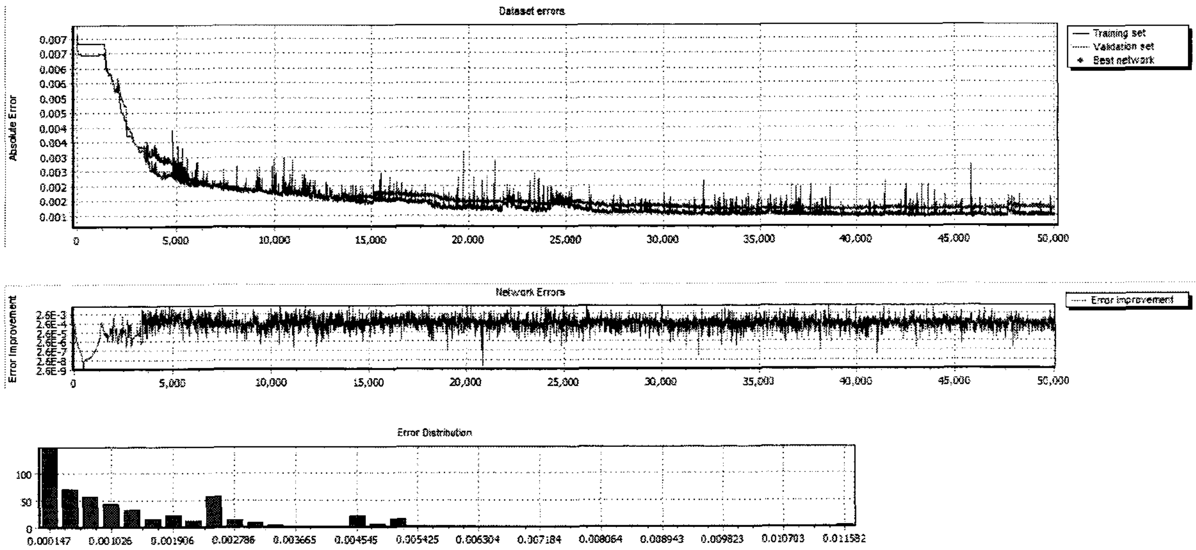
Correlation: 0.984537, R-squared: 0.967508, Training time: 0:31:10

Figure 5.1.1. Summary of training results from networks 236 (7-14-8-1)



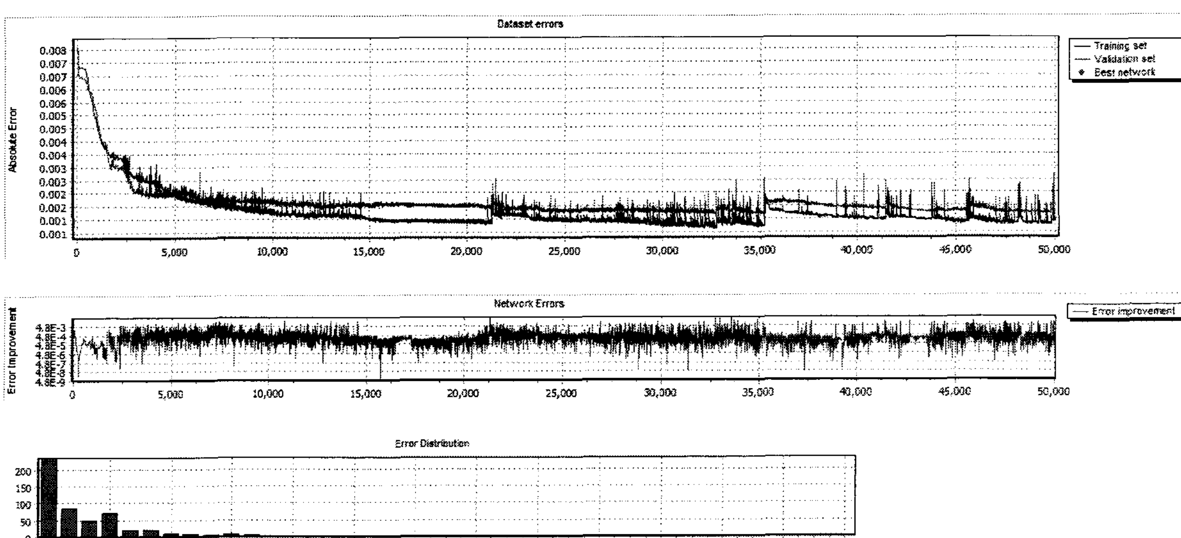
Correlation: 0.992970, R-squared: 0.985837, Training time: 1:02:17

Figure 5.1.2. Summary of training results from networks 195 (7-29-6-1)



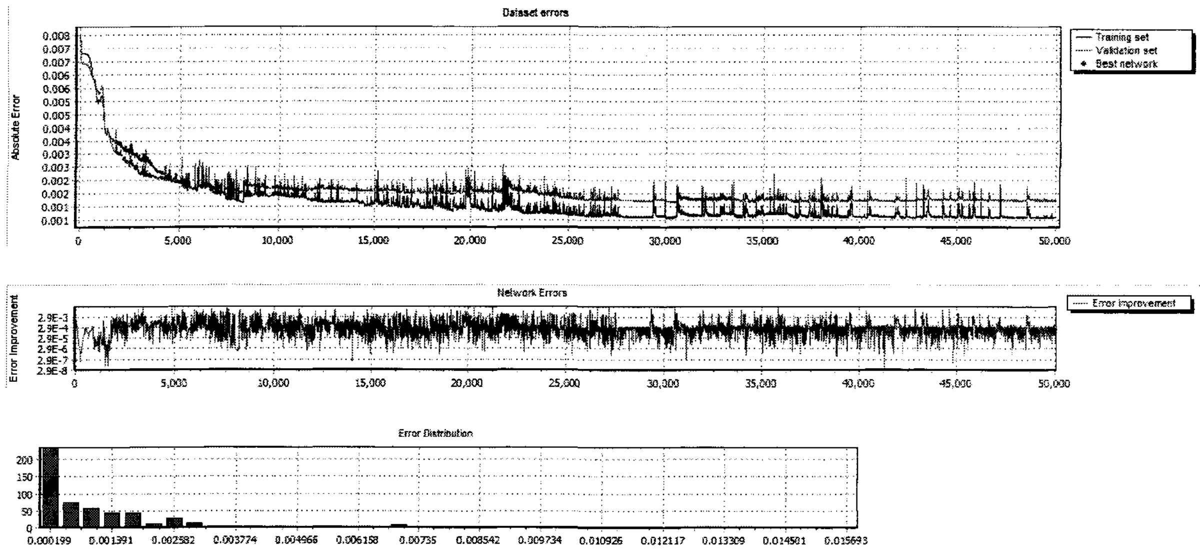
Correlation: 0.958397, R-squared: 0.913092, Training time: 0:32:52

Figure 5.1.3. Summary of training results from networks 101 (7-19-3-1)



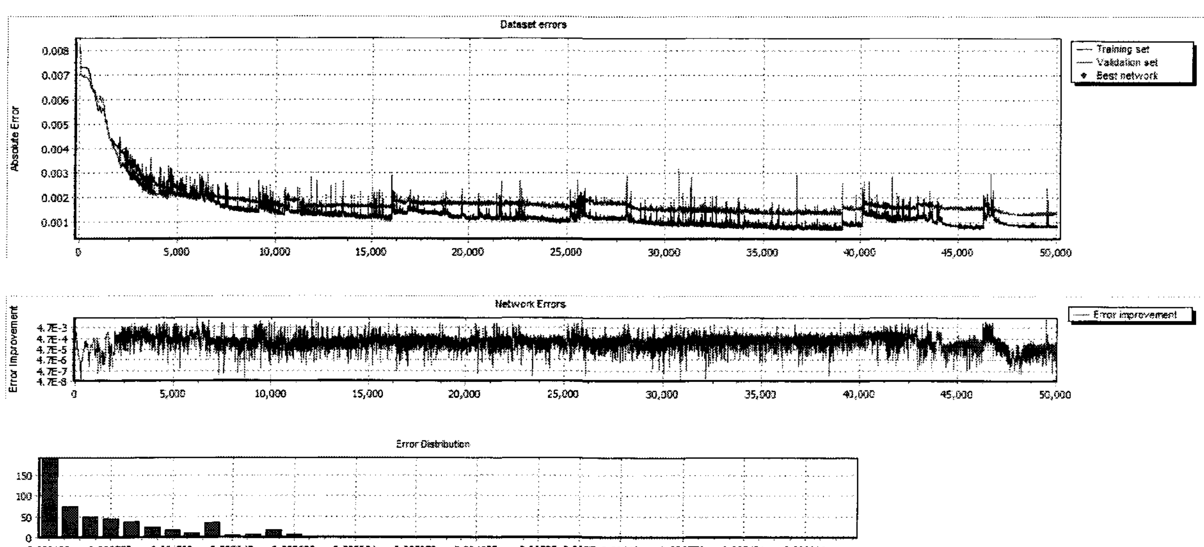
Correlation: 0.939745, R-squared: 0.874653, Training time: 0:54:16

Figure 5.1.4. Summary of training results from networks 738 (7-12-26-1)



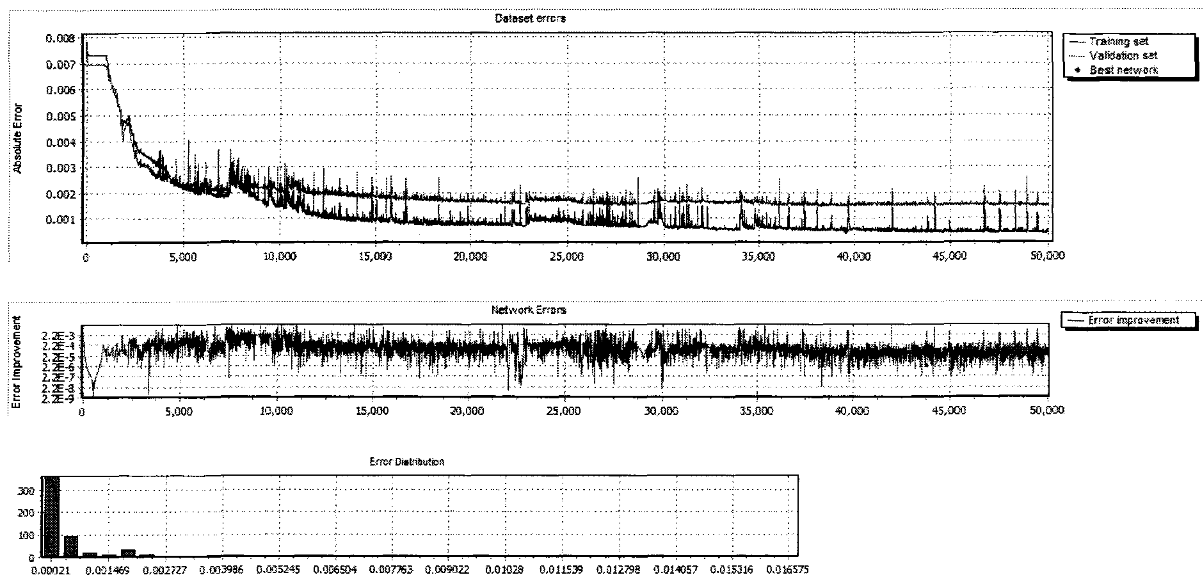
Correlation: 0.953679, R-squared: 0.903882, Training time: 0:45:41

Figure 5.1.5. Summary of training results from networks 598 (7-12-21-1)



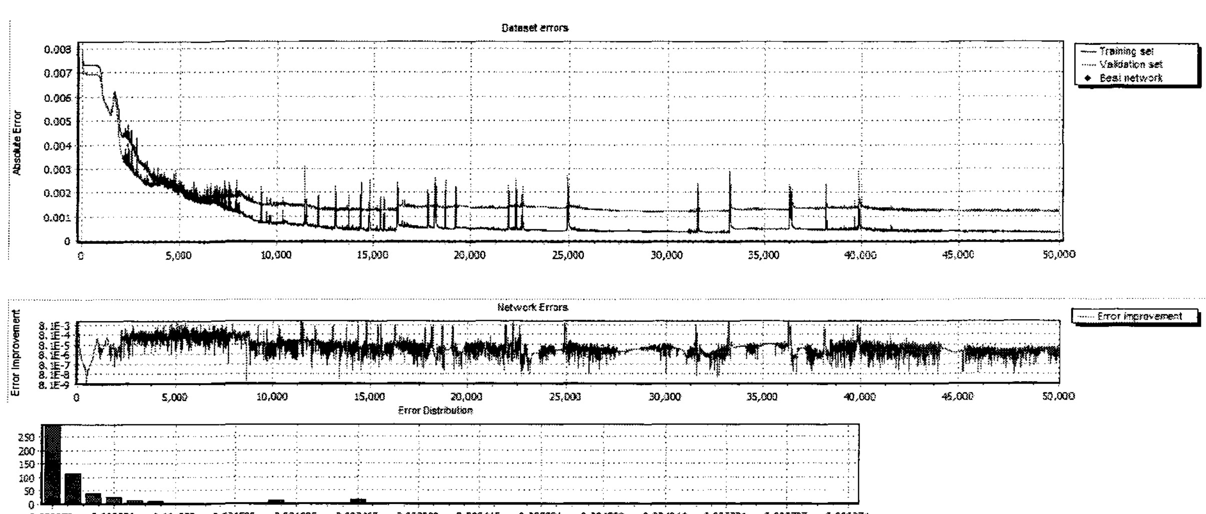
Correlation: 0.996948, R-squared: 0.99381, Training time: 1:06:13

Figure 5.1.6. Summary of training results from networks 852 (7-14-30-1)



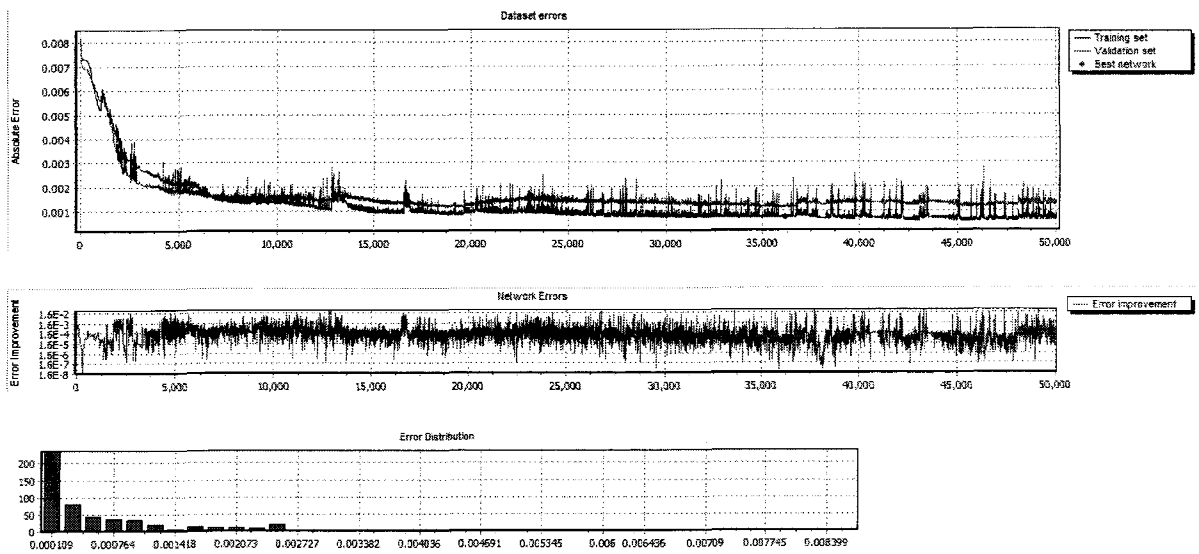
Correlation: 0.995430, R-squared: 0.990611, Training time: 0:44:52

Figure 5.1.7. Summary of training results from networks 242 (7-20-8-1)



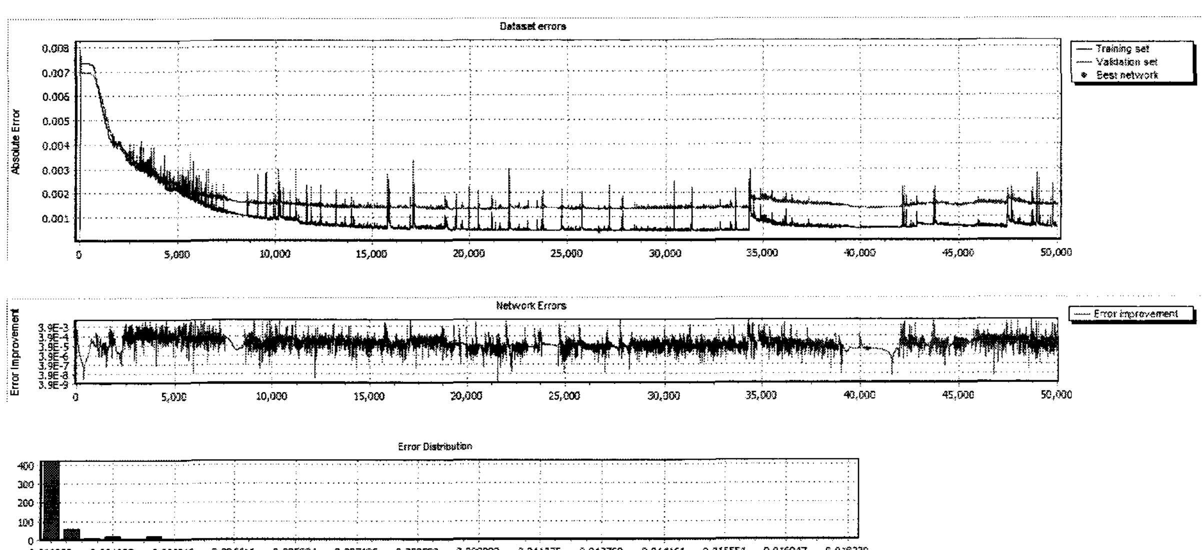
Correlation: 0.992766, R-squared: 0.985371, Training time: 0:54:12

Figure 5.1.8. Summary of training results from networks 327 (7-21-11-1)



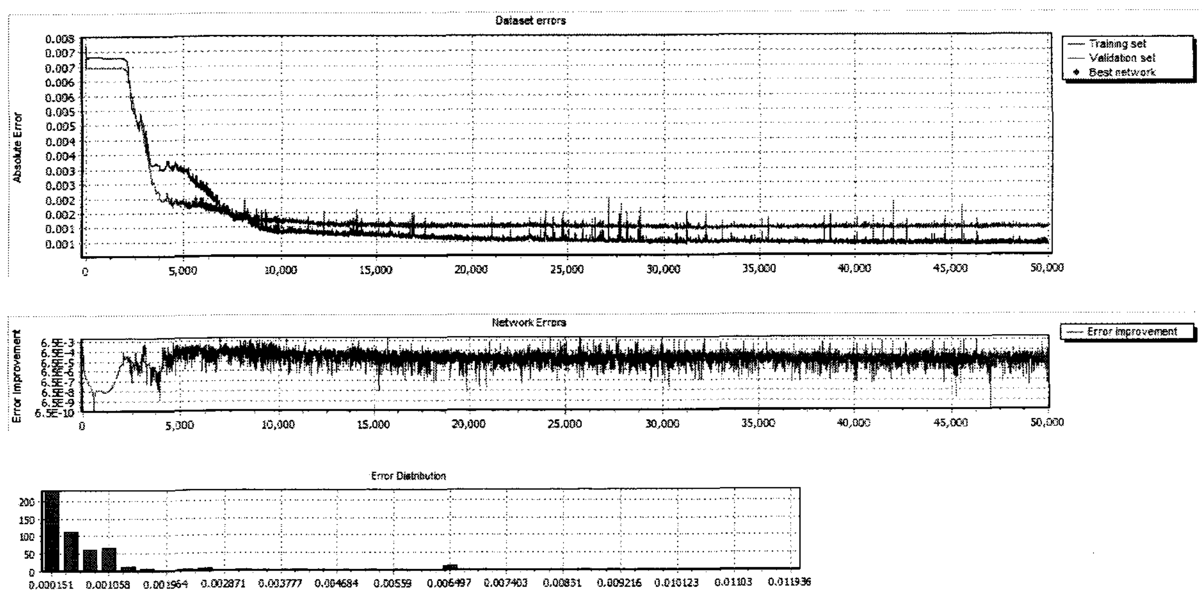
Correlation: 0.984944, R-squared: 0.968746, Training time: 1:03:34

Figure 5.1.9. Summary of training results from networks 851 (7-13-30-1)



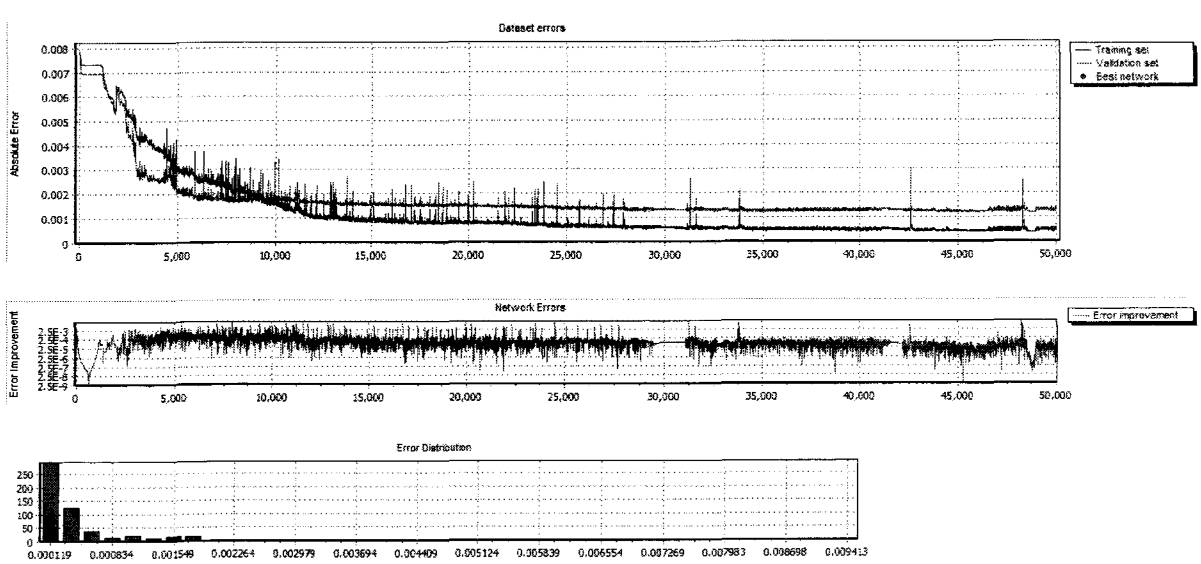
Correlation: 0.98988, R-squared: 0.97943, Training time: 0:45:25

Figure 5.1.10. Summary of training results from networks 351 (7-17-12-1)



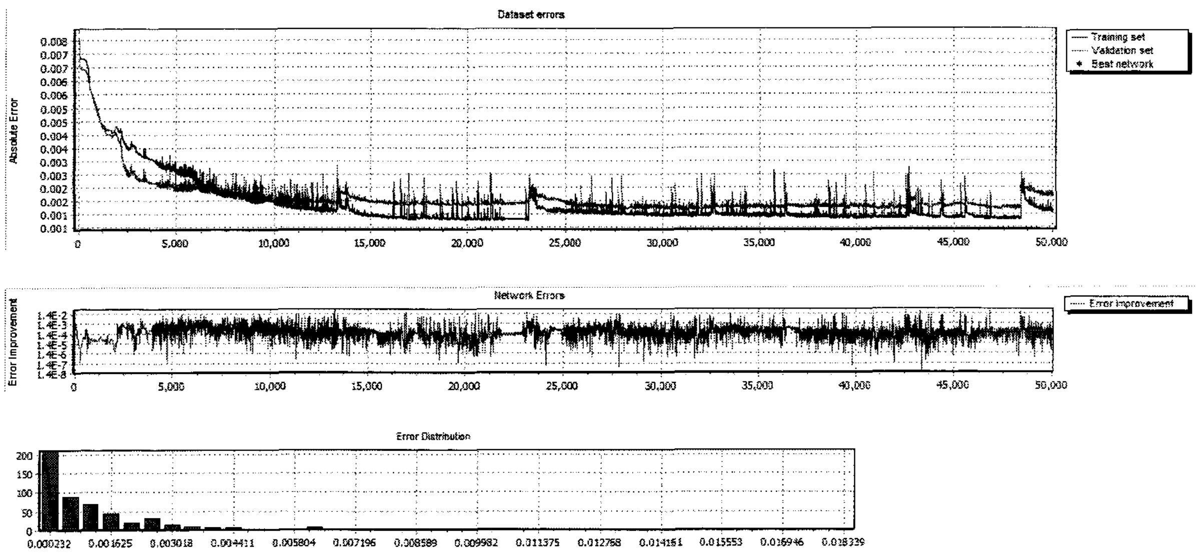
Correlation: 0.976268, R-squared: 0.948434, Training time: 0:52:33

Figure 5.1.11. Summary of training results from networks 138 (7-28-4-1)



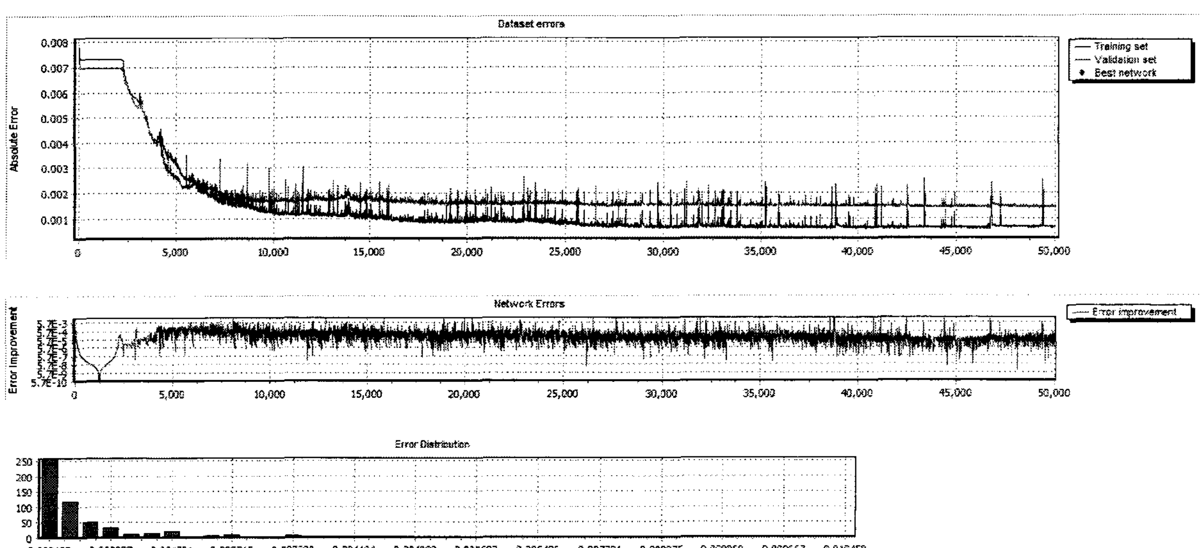
Correlation: 0.974289, R-squared: 0.945383, Training time: 0:52:51

Figure 5.1.12. Summary of training results from networks 272 (7-22-9-1)



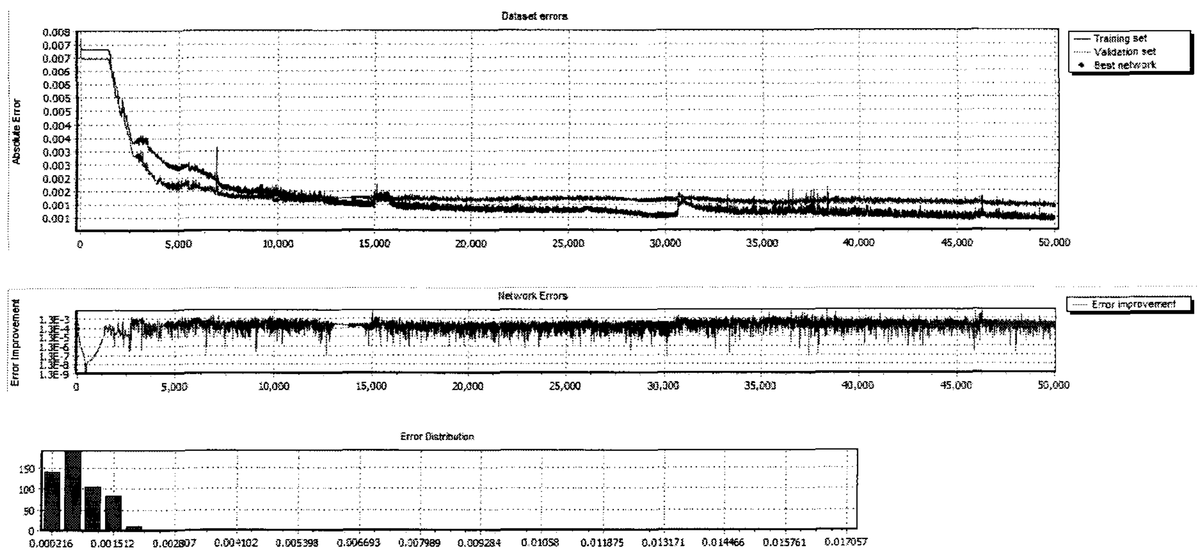
Correlation: 0.978502, R-squared: 0.955031, Training time: 0:56:34

Figure 5.1.13. Summary of training results from networks 739 (7-13-26-1)



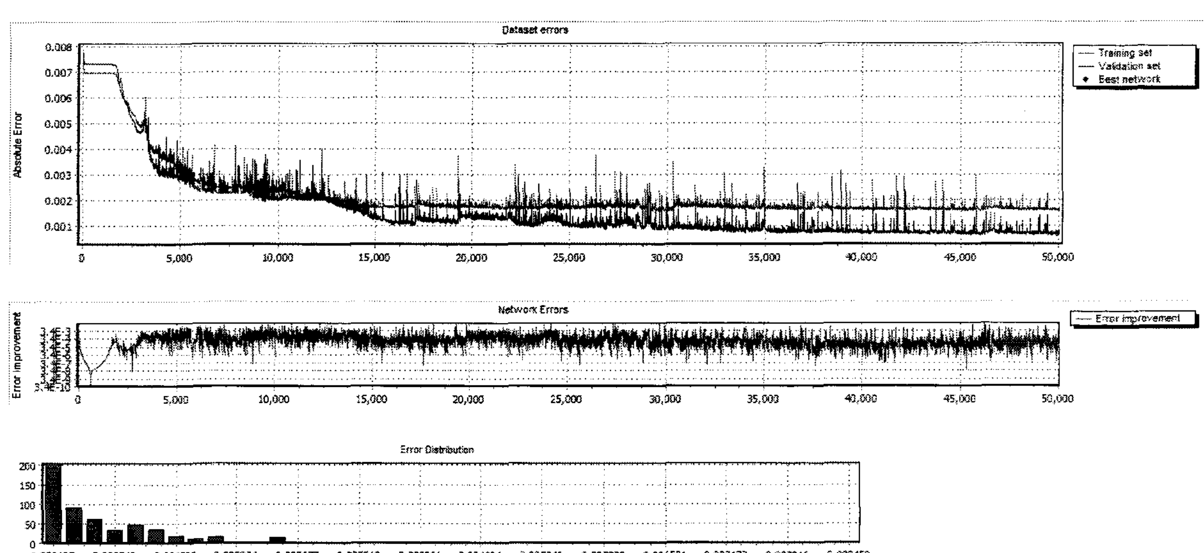
Correlation: 0.954553, R-squared: 0.903356, Training time: 0:39:43

Figure 5.1.14. Summary of training results from networks 239 (7-17-8-1)



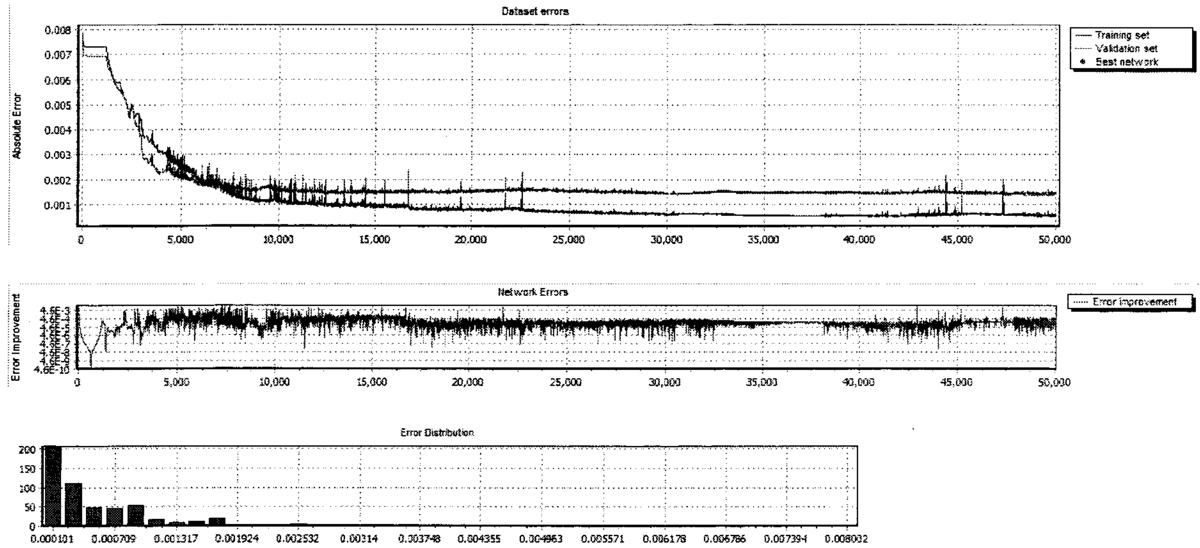
Correlation: 0.988228, R-squared: 0.976324, Training time: 0:50:35

Figure 5.1.15. Summary of training results from networks 111 (7-29-3-1)



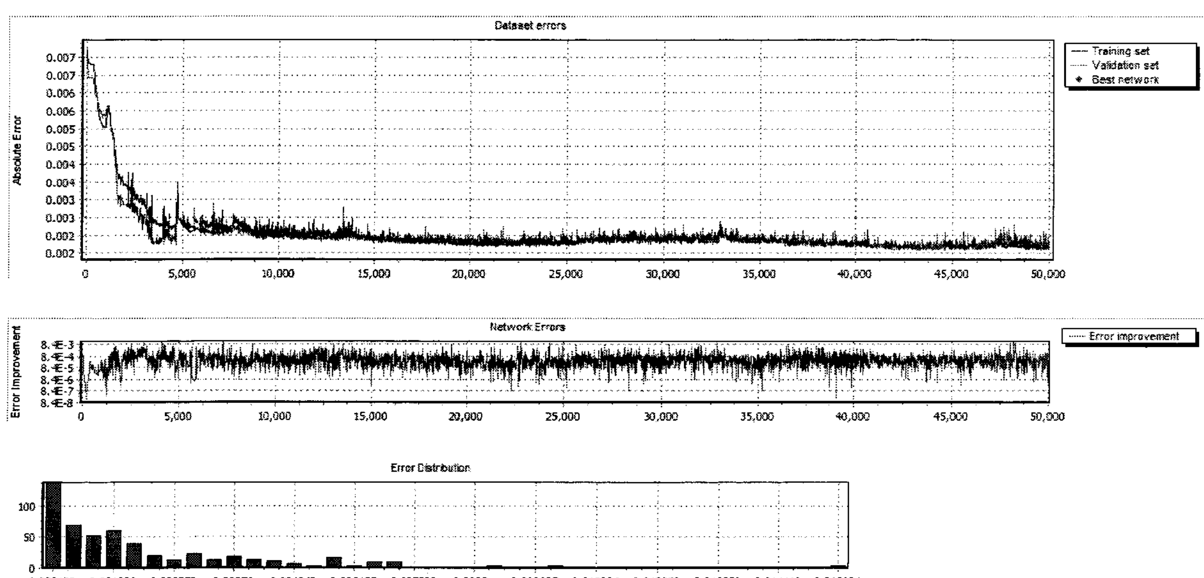
Correlation: 0.973747, R-squared: 0.946976, Training time: 0:47:30

Figure 5.1.16. Summary of training results from networks 189 (7-23-6-1)



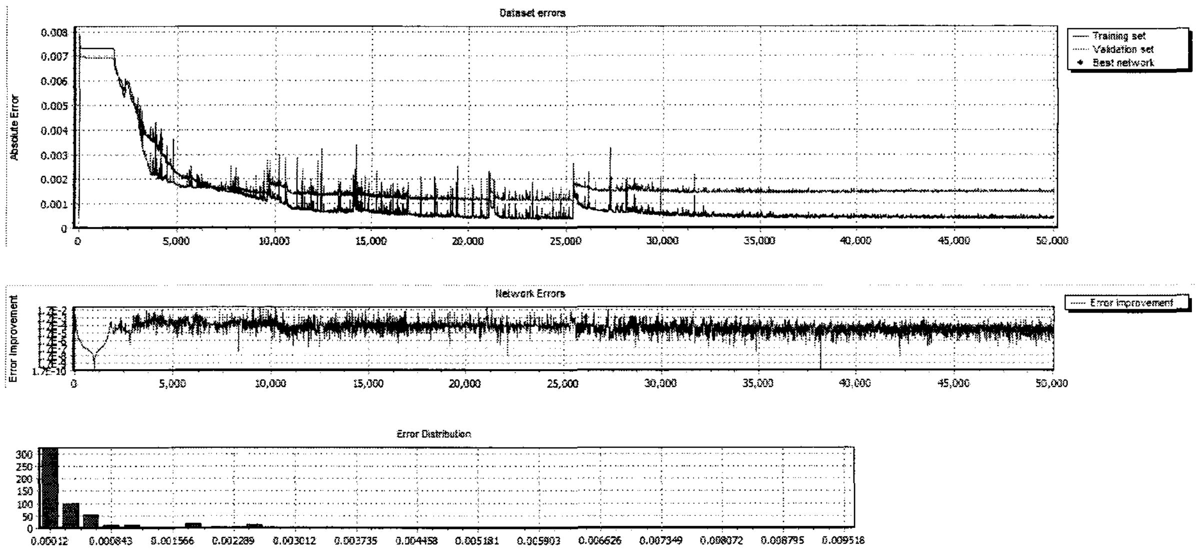
Correlation: 0.988461, R-squared: 0.976649, Training time: 0:44:27

Figure 5.1.17. Summary of training results from networks 269 (7-19-9-1)



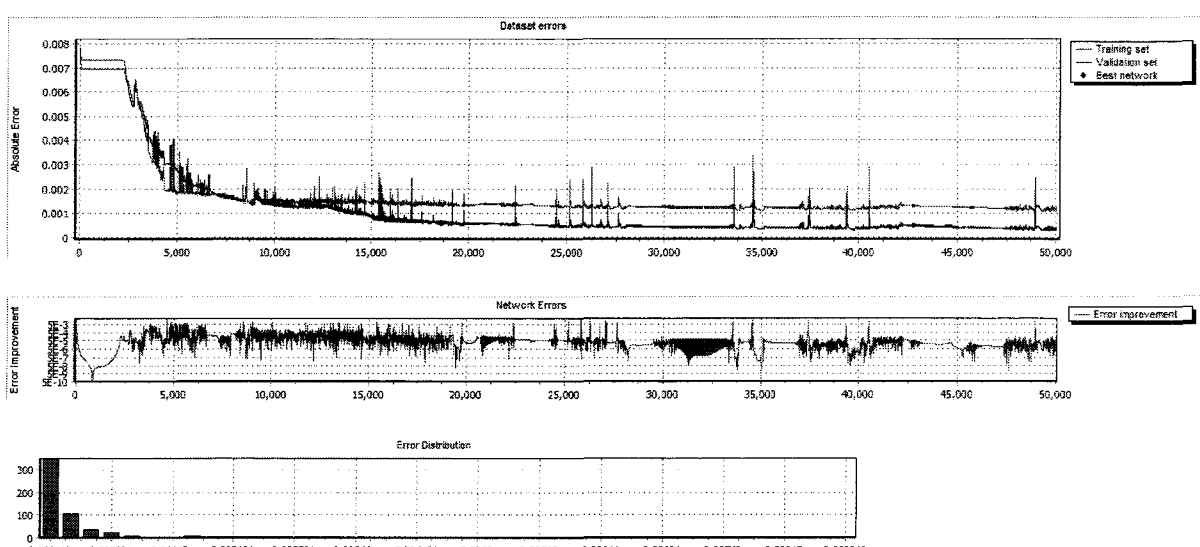
Correlation: 0.920827, R-squared: 0.831101, Training time: 0:24:21

Figure 5.1.18. Summary of training results from networks 150 (7-12-5-1)



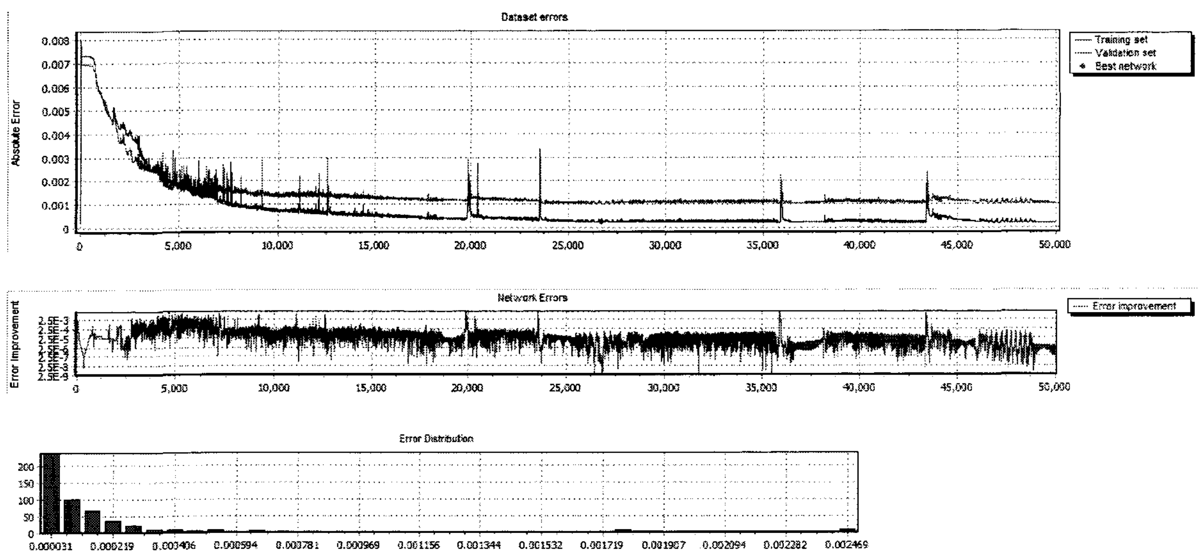
Correlation: 0.994278, R-squared: 0.988398, Training time: 0:49:47

Figure 5.1.19. Summary of training results from networks 271 (7-21-9-1)



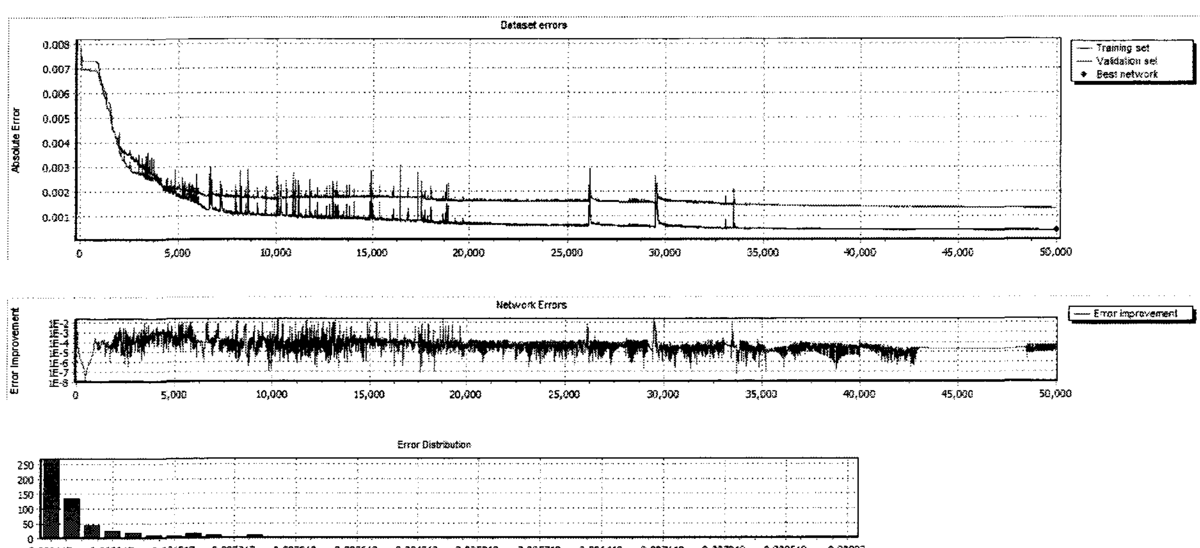
Correlation: 0.998130, R-squared: 0.996173, Training time: 0:50:50

Figure 5.1.20. Summary of training results from networks 245 (7-23-8-1)



Correlation: 0.972467, R-squared: 0.944055, Training time: 1:16:58

Figure 5.1.21. Summary of training results from networks 580 (7-22-20-1)



Correlation: 0.997069, R-squared: 0.993989, Training time: 0:42:00

Figure 5.1.22. Summary of training results from networks 267 (7-17-9-1)

Table 5.2. Summary of test results of the top 22 networks systems

ID	Architecture*	Avg training error	Avg test error	Correlation	R-Squared
236	7-14-8-1	0.000811	0.001624	0.893830	0.794020
195	7-29-6-1	0.000359	0.001162	0.906888	0.815187
101	7-19-3-1	0.001396	0.001821	0.893903	0.775369
738	7-12-26-1	0.001538	0.001556	0.921891	0.834270
598	7-12-21-1	0.001163	0.001624	0.911959	0.818016
852	7-14-30-1	0.000312	0.001030	0.934397	0.872816
242	7-20-8-1	0.000379	0.001104	0.925814	0.851820
327	7-21-11-1	0.000403	0.001080	0.919159	0.841494
851	7-13-30-1	0.000671	0.001249	0.917846	0.834396
351	7-17-12-1	0.000449	0.001261	0.906226	0.817399
138	7-28-4-1	0.000833	0.001032	0.933386	0.862882
272	7-22-9-1	0.001018	0.001372	0.909450	0.822418
739	7-13-26-1	0.000854	0.001295	0.924187	0.848112
239	7-17-8-1	0.001253	0.001437	0.910494	0.809594
111	7-29-3-1	0.000703	0.001364	0.921265	0.838768
189	7-23-6-1	0.000944	0.001333	0.916181	0.838203
269	7-19-9-1	0.000575	0.001448	0.892852	0.788818
150	7-12-5-1	0.002051	0.002102	0.882093	0.736518
271	7-21-9-1	0.000332	0.001137	0.915231	0.833103
245	**7-23-8-1**	**0.000302**	**0.001063**	**0.940371**	**0.877805**
580	7-22-20-1	0.000233	0.000976	0.932573	0.867509
267	7-17-9-1	0.000922	0.001509	0.904474	0.806428

* Input Layer – Hidden Layer 1 – Hidden Layer 2 – Output Layer

Table 5.3. Summary of test results from the neural networks model

		Predicted		
		Sharp Tool	Worn Tool	Total
Observed	Sharp Tool	**57**	5	62
	Worn Tool	0	**89**	89
	Total	57	94	151

Number of sharp tool samples predicted accurately: 57 out of 62 (92% accuracy)

Number of worn tool samples predicted accurately: 89 out of 89 (100% accuracy)

Total number of tool samples predicted accurately: 146 out of 151 (97% accuracy)

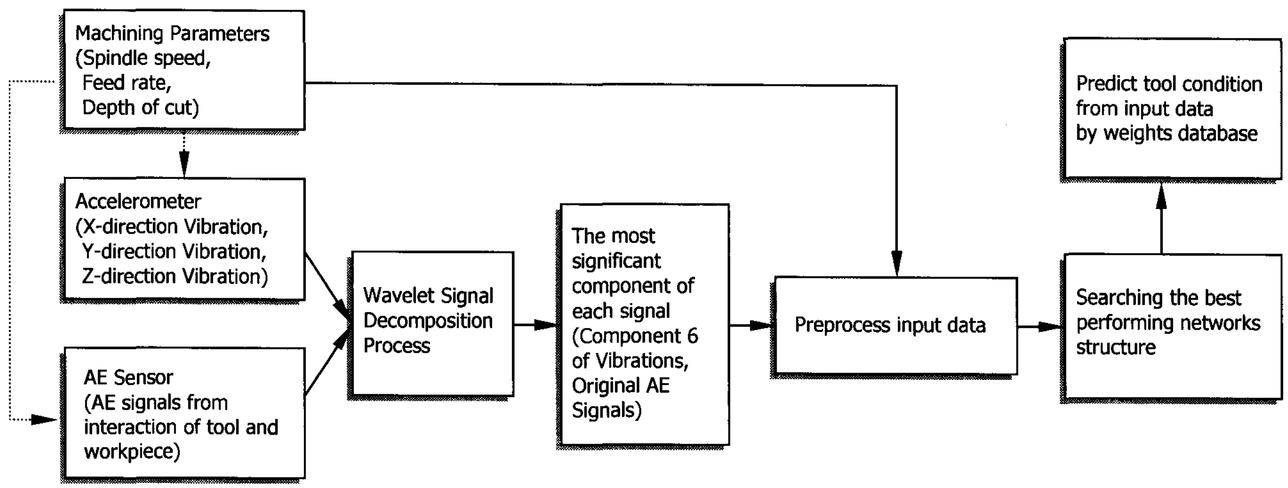


Figure 5.2. The process of ANN model operation for tool condition

CHAPTER 6. CONCLUSION

Despite the increasing needs of in-process tool condition monitoring systems in metal cutting manufacturing industries to eliminate or minimize the defect part caused by a tool that was failed to be identified as "worn tool," a limited number of studies showed the economical yet successful integration capacity of its proposed systems (Chen & Chen, 2002; Jemielniak, 1999). In this study, a tri-accelerometer and AE sensor, the most cost effective and accessible sensors in the current market, were proposed as the sensors for an in-direct tool monitoring system. To minimize the disadvantage of the in-direct sensing method for tool condition monitoring — the higher integration of noise factor from the signals obtained — a signal process and statistical technique was proposed. Also, by utilizing the processed signals, two in-process tool condition monitoring systems were developed. Following is the summary of the findings of this study.

1. Wavelet transformation method decomposed the low signals of the tri-axial accelerometer and AE sensor into six components each. From the statistical analysis, components 6 of the x, y, and z direction vibration signals and the raw signal of AE sensor were found to be the most significant signal components related to the tool condition of turning operations.
2. By eliminating the effects of the machining parameters (spindle speed, feed rate, and depth of cut) from each signal, a 12.6% increase in prediction capability was found from the statistical multiple regression model, compared with disregarding the machining parameter effects from the signals.

3. The developed statistical multiple regression model showed 90% accuracy to detect tool condition from 151 tests when it was adopted as a “STOP-GO” tool with the reject flank wear amount of 0.00787 inch (0.2 mm) or bigger.
4. A noble approach was proposed to find the best-performing neural networks structure for tool condition monitoring system. From the method, 7-23-8-1 (input layer-hidden layer 1-hidden layer 2-output layer) structure was found to be the best-performing networks system for the tool condition monitoring system.
5. The developed artificial neural networks-based tool condition monitoring system (ANN-TCMS) showed 97% accuracy to detect the tool condition from 151 tests when it was adopted as a “STOP-GO” tool with the rejected flank wear amount of 0.00787 inch (0.2 mm) or bigger.
6. The two developed systems showed high-accuracy prediction capabilities, so the systems can be adopted as in-process tool condition monitoring systems to meet the needs of the cost-effective means to prevent defects and provide optimized tool usage strategy in the metal cutting industry.

Recommendation for Further Studies

This study showed the successful development of an in-process tool condition monitoring system. However, there were limitations to resolve to integrate the developed in-process tool condition monitoring systems into the current CNC technologies. The following are recommendations for further studies in the in-process tool condition monitoring system development in CNC lathe machines.

1. The adoption of trial-accelerometer and an AE sensor showed successful results. However, a need for further study for sensor mounting and shield method was found, to eliminate the interference of chips created during the cutting process.
2. In this study, the raw signals were decomposed into six components. To test the performance of variable ranges of signal components, testing the decompositions with different numbers of components and the correlations between the components with tool conditions is recommended.
3. In this study, the numbers of hidden layers and nodes in the neural networks were limited to 2 (hidden layers) and 30 (nodes in each hidden layer). Series of tests with the advanced structures, with an increased number of hidden layers and neurons, are recommended to evaluate the performance of the extended neural networks for the tool condition monitoring system.
4. In this study, limited tool conditions, machining parameters, and workpiece materials were utilized. To adopt the system in the industry, enlarging the number of tool conditions and machining parameters with various materials is recommended, to build a wider-range database for the tool condition monitoring system.
5. The development of the tool condition monitoring system showed the capacity of detecting the signals and tool conditions without machining interruption. However, the monitoring systems were developed off-process because of limitations of the process of developing the models. A further study of a concurrent system integrating data acquisition, signal process, and neural-networks training simultaneously for true in-process monitoring is recommended.

APPENDIX A. NC PROGRAM

```
%
O0001
N100 T0101
N110 G97 Sxxx M3
N120 Fxxx
N130 G0 X1.55 Z.05
N140 G1 Xxxx
N150 G1 Z-1.0
N160 G0 X1.55
N170 G0 Z.05
N180 T0100
N190 G28 U0. W0.
N420 M30
%
```

where Sxxx sets spindle speed in xxx rpm
Fxxx sets feed rate in xxx inch/rev
Xxxx sets depth of cut in xxx inch diameter of workpiece

APPENDIX B. EXPERIMENT RESULTS

TRAIN DATA

Exp #	S	F	D	X	Y	Z	W	Tool Wear
1	500	0.01	0.01	0.181144	-1.376240	0.146925	0.478240	0.003571
2	500	0.01	0.01	0.205166	-1.336740	0.145085	0.517583	0.003571
3	500	0.01	0.01	0.197664	-1.406050	0.128546	0.557175	0.003571
4	500	0.01	0.02	0.317035	-1.063200	0.242393	0.607634	0.003571
5	500	0.01	0.02	0.304418	-1.106880	0.268476	0.831582	0.003571
6	500	0.01	0.02	0.315304	-1.086400	0.232679	0.814946	0.003571
7	500	0.01	0.03	0.368386	-1.093060	0.433740	0.679878	0.003571
8	500	0.01	0.03	0.400395	-1.040390	0.411845	0.635852	0.003571
9	500	0.01	0.03	0.414392	-1.019300	0.442722	0.610294	0.003571
10	500	0.02	0.01	0.102622	-1.370820	0.097157	0.424932	0.003571
11	500	0.02	0.01	0.083710	-1.404250	0.069873	0.305184	0.003571
12	500	0.02	0.01	0.077454	-1.400390	0.063131	0.265597	0.003571
13	500	0.02	0.02	0.269638	-1.161640	0.290448	0.747379	0.003571
14	500	0.02	0.02	0.293011	-1.172640	0.259671	0.645238	0.003571
15	500	0.02	0.02	0.299093	-1.112300	0.272568	0.654367	0.003571
16	500	0.02	0.03	0.316299	-1.032650	0.379247	0.502651	0.003571
17	500	0.02	0.03	0.332007	-1.067560	0.350215	0.630114	0.003571
18	500	0.02	0.03	0.281743	-0.996404	0.365590	0.542201	0.003571
19	500	0.03	0.01	0.158816	-1.316920	0.120599	0.336818	0.003571
20	500	0.03	0.01	0.158962	-1.319400	0.117991	0.363211	0.003571
21	500	0.03	0.01	0.145745	-1.323340	0.103880	0.414540	0.003571
22	500	0.03	0.02	0.154426	-1.270400	0.145945	0.226132	0.003571
23	500	0.03	0.02	0.176771	-1.294310	0.129439	0.207231	0.003571
24	500	0.03	0.02	0.171970	-1.285010	0.124149	0.192357	0.003571
25	500	0.03	0.03	0.304220	-1.151320	0.357713	0.484727	0.003571
26	500	0.03	0.03	0.281967	-1.113560	0.439677	0.408110	0.003571
27	500	0.03	0.03	0.262336	-1.120260	0.296480	0.386981	0.003571
28	1000	0.01	0.01	0.068667	-1.437000	0.059092	0.214819	0.003571
29	1000	0.01	0.01	0.067852	-1.433030	0.056220	0.246632	0.003571
30	1000	0.01	0.01	0.060224	-1.432590	0.038731	0.293512	0.003571
31	1000	0.01	0.02	0.224355	-1.161570	0.248029	0.569686	0.003571
32	1000	0.01	0.02	0.217729	-1.178080	0.263176	0.651630	0.003571
33	1000	0.01	0.02	0.251936	-1.178030	0.249563	0.725528	0.003571
34	1000	0.01	0.03	0.158113	-1.310390	0.188489	0.313797	0.003571
35	1000	0.01	0.03	0.150322	-1.329730	0.166520	0.284133	0.003571
36	1000	0.01	0.03	0.144316	-1.316330	0.157925	0.357426	0.003571
37	1000	0.02	0.01	0.158027	-1.296940	0.175922	0.691881	0.003571
38	1000	0.02	0.01	0.167136	-1.290010	0.165296	0.363212	0.003571
39	1000	0.02	0.01	0.169910	-1.256000	0.160453	0.539865	0.003571
40	1000	0.02	0.02	0.141500	-1.319100	0.152018	0.411276	0.003571
41	1000	0.02	0.02	0.108274	-1.338600	0.126805	0.485439	0.003571
42	1000	0.02	0.02	0.133174	-1.351400	0.117960	0.426591	0.003571
43	1000	0.02	0.03	0.085654	-1.405220	0.086203	0.214191	0.003571
44	1000	0.02	0.03	0.084271	-1.409640	0.069609	0.206070	0.003571
45	1000	0.02	0.03	0.079407	-1.413020	0.055348	0.213611	0.003571
46	1000	0.03	0.01	0.139626	-1.335970	0.147725	0.513354	0.003571

Exp #	S	F	D	X	Y	Z	W	Tool Wear
47	1000	0.03	0.01	0.132668	-1.315710	0.138365	0.414356	0.003571
48	1000	0.03	0.01	0.133713	-1.338210	0.106116	0.462755	0.003571
49	1000	0.03	0.02	0.190189	-1.239410	0.195441	0.301361	0.003571
50	1000	0.03	0.02	0.187736	-1.277720	0.159303	0.406668	0.003571
51	1000	0.03	0.02	0.181478	-1.250680	0.165595	0.403881	0.003571
52	1000	0.03	0.03	0.125367	-1.339310	0.121796	0.323578	0.003571
53	1000	0.03	0.03	0.118954	-1.330810	0.124073	0.401772	0.003571
54	1000	0.03	0.03	0.122328	-1.340130	0.117293	0.383619	0.003571
55	1500	0.01	0.01	0.196750	-1.247170	0.226735	0.828470	0.003571
56	1500	0.01	0.01	0.206262	-1.237700	0.233016	0.612253	0.003571
57	1500	0.01	0.01	0.207576	-1.219080	0.208752	0.585239	0.003571
58	1500	0.01	0.02	0.080566	-1.415180	0.082887	0.293829	0.003571
59	1500	0.01	0.02	0.087546	-1.419260	0.066207	0.340228	0.003571
60	1500	0.01	0.02	0.080182	-1.422140	0.050721	0.242547	0.003571
61	1500	0.01	0.03	0.073822	-1.441900	0.066318	0.156032	0.003571
62	1500	0.01	0.03	0.066105	-1.431650	0.059604	0.154097	0.003571
63	1500	0.01	0.03	0.067400	-1.441100	0.041189	0.138197	0.003571
64	1500	0.02	0.01	0.085215	-1.401359	0.062450	0.230076	0.003571
65	1500	0.02	0.01	0.082527	-1.396767	0.052630	0.322605	0.003571
66	1500	0.02	0.01	0.085178	-1.400204	0.044106	0.246875	0.003571
67	1500	0.02	0.02	0.075085	-1.425840	0.067797	0.434304	0.003571
68	1500	0.02	0.02	0.073952	-1.437130	0.055910	0.249600	0.003571
69	1500	0.02	0.02	0.075865	-1.429730	0.039622	0.313889	0.003571
70	1500	0.02	0.03	0.130537	-1.355450	0.108952	0.376022	0.003571
71	1500	0.02	0.03	0.103511	-1.368310	0.081063	0.377905	0.003571
72	1500	0.02	0.03	0.110050	-1.363490	0.087263	0.481548	0.003571
73	1500	0.03	0.01	0.075882	-1.429730	0.073620	0.231379	0.003571
74	1500	0.03	0.01	0.065926	-1.432550	0.051680	0.258201	0.003571
75	1500	0.03	0.01	0.066417	-1.435110	0.041827	0.198744	0.003571
76	1500	0.03	0.02	0.058421	-1.445400	0.053786	0.230983	0.003571
77	1500	0.03	0.02	0.062167	-1.438640	0.041851	0.288749	0.003571
78	1500	0.03	0.02	0.056543	-1.438120	0.028906	0.361142	0.003571
79	1500	0.03	0.03	0.060072	-1.455330	0.056816	0.131700	0.003571
80	1500	0.03	0.03	0.058690	-1.453910	0.043528	0.146328	0.003571
81	1500	0.03	0.03	0.054848	-1.450520	0.028636	0.178431	0.003571
82	500	0.01	0.01	0.116101	-1.432510	0.117676	0.472252	0.010714
83	500	0.01	0.01	0.102338	-1.425920	0.111031	0.483291	0.010714
84	500	0.01	0.01	0.115058	-1.424800	0.106873	0.439040	0.010714
85	500	0.01	0.02	0.202744	-1.263670	0.241751	0.422320	0.010714
86	500	0.01	0.02	0.204127	-1.277260	0.246862	0.484142	0.010714
87	500	0.01	0.02	0.193513	-1.298830	0.231847	0.516682	0.010714
88	500	0.01	0.03	0.240857	-1.236190	0.294200	0.659842	0.010714
89	500	0.01	0.03	0.235760	-1.247390	0.281976	0.515375	0.010714
90	500	0.01	0.03	0.257110	-1.254950	0.270639	0.760654	0.010714
91	500	0.02	0.01	0.182275	-1.371140	0.128162	0.208015	0.010714
92	500	0.02	0.01	0.177945	-1.407270	0.093313	0.210228	0.010714
93	500	0.02	0.01	0.163999	-1.365710	0.116563	0.269201	0.010714
94	500	0.02	0.02	0.174021	-1.313460	0.211754	0.806920	0.010714
95	500	0.02	0.02	0.185493	-1.338860	0.184625	0.724539	0.010714
96	500	0.02	0.02	0.174450	-1.334510	0.195865	0.652516	0.010714
97	500	0.02	0.03	0.205464	-1.288030	0.245414	0.613685	0.010714

Exp #	S	F	D	X	Y	Z	W	Tool Wear
98	500	0.02	0.03	0.221732	-1.306630	0.239846	0.547195	0.010714
99	500	0.02	0.03	0.200193	-1.275760	0.267396	0.575885	0.010714
100	500	0.03	0.01	0.117029	-1.424740	0.133568	0.189153	0.010714
101	500	0.03	0.01	0.109949	-1.407650	0.111245	0.231195	0.010714
102	500	0.03	0.01	0.114484	-1.407980	0.100680	0.285502	0.010714
103	500	0.03	0.02	0.138160	-1.390300	0.134171	0.306749	0.010714
104	500	0.03	0.02	0.136128	-1.364890	0.116173	0.272853	0.010714
105	500	0.03	0.02	0.126721	-1.353800	0.114372	0.218970	0.010714
106	500	0.03	0.03	0.176092	-1.305390	0.204296	0.278864	0.010714
107	500	0.03	0.03	0.198795	-1.246570	0.221146	0.403999	0.010714
108	500	0.03	0.03	0.195917	-1.281740	0.194523	0.395110	0.010714
109	1000	0.01	0.01	0.161227	-1.368270	0.107846	0.603167	0.010714
110	1000	0.01	0.01	0.137414	-1.379280	0.089888	0.540450	0.010714
111	1000	0.01	0.01	0.133979	-1.390390	0.060854	0.448093	0.010714
112	1000	0.01	0.02	0.121700	-1.357470	0.157365	0.410670	0.010714
113	1000	0.01	0.02	0.127882	-1.393640	0.149672	0.506186	0.010714
114	1000	0.01	0.02	0.144596	-1.332700	0.146068	0.507462	0.010714
115	1000	0.01	0.03	0.104174	-1.425860	0.113769	0.352319	0.010714
116	1000	0.01	0.03	0.123717	-1.444280	0.108903	0.319536	0.010714
117	1000	0.01	0.03	0.131909	-1.401500	0.117820	0.288947	0.010714
118	1000	0.02	0.01	0.107286	-1.484520	0.058490	0.216505	0.010714
119	1000	0.02	0.01	0.107858	-1.481520	0.039455	0.368819	0.010714
120	1000	0.02	0.01	0.103689	-1.473160	0.045804	0.269628	0.010714
121	1000	0.02	0.02	0.090588	-1.483290	0.096876	0.379594	0.010714
122	1000	0.02	0.02	0.085717	-1.485610	0.082124	0.403208	0.010714
123	1000	0.02	0.02	0.074832	-1.514970	0.053863	0.359011	0.010714
124	1000	0.02	0.03	0.080138	-1.495810	0.077783	0.175596	0.010714
125	1000	0.02	0.03	0.077557	-1.500260	0.059948	0.210634	0.010714
126	1000	0.02	0.03	0.084272	-1.483280	0.048403	0.169810	0.010714
127	1000	0.03	0.01	0.121735	-1.408360	0.136854	0.348266	0.010714
128	1000	0.03	0.01	0.117320	-1.414030	0.109632	0.495587	0.010714
129	1000	0.03	0.01	0.115835	-1.428600	0.089026	0.357344	0.010714
130	1000	0.03	0.02	0.144299	-1.367090	0.151217	0.312538	0.010714
131	1000	0.03	0.02	0.158200	-1.341010	0.144224	0.390743	0.010714
132	1000	0.03	0.02	0.147490	-1.363020	0.143865	0.392018	0.010714
133	1000	0.03	0.03	0.108376	-1.420160	0.104100	0.344893	0.010714
134	1000	0.03	0.03	0.113978	-1.417200	0.091442	0.435722	0.010714
135	1000	0.03	0.03	0.112136	-1.416900	0.099155	0.406492	0.010714
136	1500	0.01	0.01	0.135252	-1.359000	0.141712	0.545348	0.010714
137	1500	0.01	0.01	0.147371	-1.346670	0.138065	0.716227	0.010714
138	1500	0.01	0.01	0.156291	-1.364540	0.145850	0.714337	0.010714
139	1500	0.01	0.02	0.074123	-1.474680	0.070831	0.243584	0.010714
140	1500	0.01	0.02	0.069787	-1.459130	0.061843	0.298304	0.010714
141	1500	0.01	0.02	0.070016	-1.467300	0.046503	0.266003	0.010714
142	1500	0.01	0.03	0.063178	-1.483440	0.062081	0.167831	0.010714
143	1500	0.01	0.03	0.060730	-1.477590	0.047796	0.166837	0.010714
144	1500	0.01	0.03	0.057163	-1.466740	0.042851	0.144612	0.010714
145	1500	0.02	0.01	0.082670	-1.432240	0.086608	0.252869	0.010714
146	1500	0.02	0.01	0.085352	-1.414300	0.078722	0.334444	0.010714
147	1500	0.02	0.01	0.089403	-1.418100	0.072398	0.254576	0.010714
148	1500	0.02	0.02	0.093123	-1.439050	0.082007	0.273373	0.010714

Exp #	S	F	D	X	Y	Z	W	Tool Wear
149	1500	0.02	0.02	0.085213	-1.435620	0.074261	0.237237	0.010714
150	1500	0.02	0.02	0.090004	-1.445300	0.059677	0.196381	0.010714
151	1500	0.02	0.03	0.117397	-1.377820	0.125053	0.334321	0.010714
152	1500	0.02	0.03	0.132916	-1.344960	0.109700	0.427935	0.010714
153	1500	0.02	0.03	0.116776	-1.370870	0.092591	0.263557	0.010714
154	1500	0.03	0.01	0.097080	-1.418360	0.093053	0.212739	0.010714
155	1500	0.03	0.01	0.089649	-1.432910	0.070508	0.208543	0.010714
156	1500	0.03	0.01	0.085260	-1.427520	0.056705	0.221585	0.010714
157	1500	0.03	0.02	0.091760	-1.432410	0.073412	0.233092	0.010714
158	1500	0.03	0.02	0.082248	-1.442380	0.064138	0.171560	0.010714
159	1500	0.03	0.02	0.081627	-1.442770	0.051505	0.179452	0.010714
160	1500	0.03	0.03	0.057790	-1.468720	0.044889	0.209803	0.010714
161	1500	0.03	0.03	0.056956	-1.466110	0.032009	0.279202	0.010714
162	1500	0.03	0.03	0.052607	-1.466640	0.021892	0.303639	0.010714
163	500	0.01	0.01	0.107101	-1.362730	0.118430	0.442076	0.017857
164	500	0.01	0.01	0.101658	-1.361320	0.113868	0.410997	0.017857
165	500	0.01	0.01	0.111900	-1.301120	0.117589	0.428244	0.017857
166	500	0.01	0.02	0.214369	-1.218980	0.267427	0.672320	0.017857
167	500	0.01	0.02	0.200404	-1.173730	0.262668	0.486750	0.017857
168	500	0.01	0.02	0.220860	-1.196180	0.223187	0.552450	0.017857
169	500	0.01	0.03	0.272580	-1.194180	0.273436	0.743601	0.017857
170	500	0.01	0.03	0.256455	-1.207580	0.247999	0.619583	0.017857
171	500	0.01	0.03	0.268437	-1.182120	0.267149	0.612205	0.017857
172	500	0.02	0.01	0.156555	-1.409690	0.083923	0.256485	0.017857
173	500	0.02	0.01	0.169705	-1.395630	0.088598	0.198646	0.017857
174	500	0.02	0.01	0.156136	-1.403380	0.088100	0.272347	0.017857
175	500	0.02	0.02	0.166444	-1.373860	0.210427	0.845533	0.017857
176	500	0.02	0.02	0.166817	-1.394920	0.176202	0.799637	0.017857
177	500	0.02	0.02	0.163115	-1.360410	0.173381	0.872702	0.017857
178	500	0.02	0.03	0.239533	-1.309550	0.256738	0.590175	0.017857
179	500	0.02	0.03	0.231557	-1.293460	0.283797	0.537577	0.017857
180	500	0.02	0.03	0.216126	-1.310490	0.251760	0.597974	0.017857
181	500	0.03	0.01	0.117879	-1.511720	0.119009	0.230073	0.017857
182	500	0.03	0.01	0.107594	-1.511330	0.117635	0.267680	0.017857
183	500	0.03	0.01	0.114780	-1.514170	0.099775	0.377523	0.017857
184	500	0.03	0.02	0.134611	-1.443340	0.107456	0.216891	0.017857
185	500	0.03	0.02	0.146349	-1.444940	0.107025	0.195507	0.017857
186	500	0.03	0.02	0.142224	-1.427980	0.097650	0.180585	0.017857
187	500	0.03	0.03	0.070193	-1.424280	0.071384	0.392428	0.017857
188	500	0.03	0.03	0.071517	-1.414910	0.064654	0.374044	0.017857
189	500	0.03	0.03	0.069477	-1.387570	0.054673	0.372198	0.017857
190	1000	0.01	0.01	0.161363	-1.344710	0.166297	0.477101	0.017857
191	1000	0.01	0.01	0.147810	-1.315580	0.169613	0.529715	0.017857
192	1000	0.01	0.01	0.158934	-1.344170	0.144473	0.569721	0.017857
193	1000	0.01	0.02	0.121819	-1.420080	0.142973	0.434565	0.017857
194	1000	0.01	0.02	0.132199	-1.414590	0.132202	0.444245	0.017857
195	1000	0.01	0.02	0.137512	-1.373130	0.123662	0.469850	0.017857
196	1000	0.01	0.03	0.102483	-1.415850	0.117445	0.436529	0.017857
197	1000	0.01	0.03	0.088529	-1.445970	0.102257	0.336458	0.017857
198	1000	0.01	0.03	0.135735	-1.357430	0.140548	0.448502	0.017857
199	1000	0.02	0.01	0.129113	-1.364230	0.109400	0.441843	0.017857

Exp #	S	F	D	X	Y	Z	W	Tool Wear
200	1000	0.02	0.01	0.127367	-1.366620	0.104554	0.338856	0.017857
201	1000	0.02	0.01	0.154872	-1.369580	0.131781	0.484217	0.017857
202	1000	0.02	0.02	0.088202	-1.439970	0.075593	0.383753	0.017857
203	1000	0.02	0.02	0.087385	-1.437950	0.074001	0.583262	0.017857
204	1000	0.02	0.02	0.082447	-1.429460	0.059103	0.404523	0.017857
205	1000	0.02	0.03	0.074137	-1.443190	0.069753	0.147241	0.017857
206	1000	0.02	0.03	0.080196	-1.412730	0.074075	0.221422	0.017857
207	1000	0.02	0.03	0.071904	-1.420570	0.052002	0.216131	0.017857
208	1000	0.03	0.01	0.103838	-1.383300	0.115404	0.286577	0.017857
209	1000	0.03	0.01	0.107252	-1.394140	0.102557	0.304617	0.017857
210	1000	0.03	0.01	0.108906	-1.369160	0.097759	0.383453	0.017857
211	1000	0.03	0.02	0.127022	-1.347410	0.130123	0.300652	0.017857
212	1000	0.03	0.02	0.132815	-1.344900	0.126224	0.292110	0.017857
213	1000	0.03	0.02	0.134747	-1.319010	0.128329	0.265825	0.017857
214	1000	0.03	0.03	0.111060	-1.364780	0.115365	0.259913	0.017857
215	1000	0.03	0.03	0.116729	-1.380010	0.095352	0.341058	0.017857
216	1000	0.03	0.03	0.099222	-1.390270	0.087384	0.260739	0.017857
217	1500	0.01	0.01	0.138674	-1.327310	0.161404	0.861857	0.017857
218	1500	0.01	0.01	0.130558	-1.303790	0.143464	0.748931	0.017857
219	1500	0.01	0.01	0.141477	-1.318690	0.135637	0.716414	0.017857
220	1500	0.01	0.02	0.073309	-1.445690	0.067158	0.250755	0.017857
221	1500	0.01	0.02	0.071967	-1.443860	0.058446	0.341505	0.017857
222	1500	0.01	0.02	0.064457	-1.439290	0.047976	0.224378	0.017857
223	1500	0.01	0.03	0.059749	-1.457610	0.060425	0.181559	0.017857
224	1500	0.01	0.03	0.055558	-1.452410	0.050509	0.255463	0.017857
225	1500	0.01	0.03	0.054368	-1.451000	0.031349	0.186958	0.017857
226	1500	0.02	0.01	0.103640	-1.375090	0.105015	0.260142	0.017857
227	1500	0.02	0.01	0.099039	-1.376420	0.091943	0.298791	0.017857
228	1500	0.02	0.01	0.108358	-1.365890	0.094569	0.391616	0.017857
229	1500	0.02	0.02	0.066265	-1.454680	0.058872	0.215760	0.017857
230	1500	0.02	0.02	0.076724	-1.436750	0.049097	0.496323	0.017857
231	1500	0.02	0.02	0.061095	-1.451920	0.029540	0.288576	0.017857
232	1500	0.02	0.03	0.118135	-1.356270	0.098389	0.268123	0.017857
233	1500	0.02	0.03	0.117133	-1.363430	0.088809	0.243420	0.017857
234	1500	0.02	0.03	0.116399	-1.369080	0.080325	0.369785	0.017857
235	1500	0.03	0.01	0.060487	-1.455290	0.050666	0.314343	0.017857
236	1500	0.03	0.01	0.054985	-1.451050	0.034882	0.305898	0.017857
237	1500	0.03	0.01	0.055226	-1.459450	0.024850	0.359128	0.017857
238	1500	0.03	0.02	0.053609	-1.459080	0.046291	0.231745	0.017857
239	1500	0.03	0.02	0.051355	-1.449960	0.040958	0.214829	0.017857
240	1500	0.03	0.02	0.052560	-1.453020	0.024047	0.194349	0.017857
241	1500	0.03	0.03	0.053920	-1.451410	0.046821	0.236239	0.017857
242	1500	0.03	0.03	0.052226	-1.450150	0.033624	0.261122	0.017857
243	1500	0.03	0.03	0.051843	-1.455460	0.023851	0.198452	0.017857
244	500	0.01	0.01	0.107910	-1.474040	0.122001	0.547017	0.019643
245	500	0.01	0.01	0.114398	-1.451580	0.138510	0.508449	0.019643
246	500	0.01	0.01	0.100409	-1.472790	0.096240	0.532206	0.019643
247	500	0.01	0.02	0.205228	-1.312410	0.233647	0.478561	0.019643
248	500	0.01	0.02	0.258732	-1.264850	0.246862	0.545597	0.019643
249	500	0.01	0.02	0.222627	-1.279680	0.251458	0.700196	0.019643
250	500	0.01	0.03	0.267783	-1.278730	0.266599	0.721749	0.019643

Exp #	S	F	D	X	Y	Z	W	Tool Wear
251	500	0.01	0.03	0.252744	-1.214020	0.296789	0.755522	0.019643
252	500	0.01	0.03	0.269247	-1.253910	0.262258	0.631151	0.019643
253	500	0.02	0.01	0.156677	-1.353880	0.139706	0.210363	0.019643
254	500	0.02	0.01	0.154700	-1.372300	0.126576	0.210118	0.019643
255	500	0.02	0.01	0.153888	-1.370780	0.121503	0.185762	0.019643
256	500	0.02	0.02	0.185691	-1.358610	0.200128	0.739503	0.019643
257	500	0.02	0.02	0.172941	-1.334480	0.187677	0.802764	0.019643
258	500	0.02	0.02	0.191542	-1.306780	0.185001	0.739575	0.019643
259	500	0.02	0.03	0.259545	-1.236170	0.247840	0.559538	0.019643
260	500	0.02	0.03	0.252058	-1.226050	0.262534	0.557351	0.019643
261	500	0.02	0.03	0.235605	-1.209770	0.259440	0.671900	0.019643
262	500	0.03	0.01	0.134519	-1.415180	0.122996	0.244431	0.019643
263	500	0.03	0.01	0.113310	-1.430280	0.100363	0.196246	0.019643
264	500	0.03	0.01	0.112291	-1.428660	0.086644	0.227978	0.019643
265	500	0.03	0.02	0.122200	-1.401460	0.119859	0.259400	0.019643
266	500	0.03	0.02	0.126978	-1.396260	0.117478	0.192874	0.019643
267	500	0.03	0.02	0.132048	-1.400340	0.094083	0.251650	0.019643
268	500	0.03	0.03	0.178941	-1.313770	0.207831	0.389153	0.019643
269	500	0.03	0.03	0.177643	-1.309910	0.196130	0.310480	0.019643
270	500	0.03	0.03	0.185929	-1.255970	0.471044	0.377241	0.019643
271	1000	0.01	0.01	0.142584	-1.331630	0.131596	0.487466	0.019643
272	1000	0.01	0.01	0.155968	-1.344320	0.115774	0.596804	0.019643
273	1000	0.01	0.01	0.166762	-1.272940	0.118657	0.589807	0.019643
274	1000	0.01	0.02	0.127531	-1.395920	0.133901	0.525518	0.019643
275	1000	0.01	0.02	0.115938	-1.430180	0.117742	0.525593	0.019643
276	1000	0.01	0.02	0.120123	-1.395190	0.112463	0.525987	0.019643
277	1000	0.01	0.03	0.115419	-1.419550	0.112636	0.432940	0.019643
278	1000	0.01	0.03	0.107379	-1.446060	0.110059	0.426056	0.019643
279	1000	0.01	0.03	0.098541	-1.423300	0.097170	0.418867	0.019643
280	1000	0.02	0.01	0.126213	-1.410090	0.144572	0.263350	0.019643
281	1000	0.02	0.01	0.126844	-1.390040	0.147086	0.398290	0.019643
282	1000	0.02	0.01	0.116299	-1.400150	0.114222	0.673075	0.019643
283	1000	0.02	0.02	0.087945	-1.460380	0.082852	0.574997	0.019643
284	1000	0.02	0.02	0.092952	-1.431080	0.090656	0.714576	0.019643
285	1000	0.02	0.02	0.096845	-1.401370	0.079519	0.694266	0.019643
286	1000	0.02	0.03	0.092763	-1.427520	0.088993	0.193529	0.019643
287	1000	0.02	0.03	0.086691	-1.407300	0.083933	0.197068	0.019643
288	1000	0.02	0.03	0.094136	-1.434540	0.077198	0.234398	0.019643
289	1000	0.03	0.01	0.104140	-1.392640	0.124031	0.382215	0.019643
290	1000	0.03	0.01	0.104849	-1.401380	0.094469	0.278134	0.019643
291	1000	0.03	0.01	0.096873	-1.389670	0.084855	0.419603	0.019643
292	1000	0.03	0.02	0.132867	-1.353830	0.131028	0.372235	0.019643
293	1000	0.03	0.02	0.128293	-1.329900	0.122704	0.362649	0.019643
294	1000	0.03	0.02	0.141091	-1.311790	0.136492	0.514998	0.019643
295	1000	0.03	0.03	0.109705	-1.402950	0.108784	0.243901	0.019643
296	1000	0.03	0.03	0.119497	-1.386100	0.108146	0.303130	0.019643
297	1000	0.03	0.03	0.094405	-1.374050	0.091203	0.297022	0.019643
298	1500	0.01	0.01	0.157354	-1.285020	0.162889	0.854367	0.019643
299	1500	0.01	0.01	0.151251	-1.286100	0.155541	0.813668	0.019643
300	1500	0.01	0.01	0.149971	-1.292800	0.155566	0.891008	0.019643
301	1500	0.01	0.02	0.062998	-1.438030	0.062840	0.218194	0.019643

Exp #	S	F	D	X	Y	Z	W	Tool Wear
302	1500	0.01	0.02	0.063365	-1.433130	0.052539	0.283977	0.019643
303	1500	0.01	0.02	0.057095	-1.433690	0.041312	0.262875	0.019643
304	1500	0.01	0.03	0.059461	-1.427890	0.079503	0.278038	0.019643
305	1500	0.01	0.03	0.091472	-1.322860	0.089105	0.403171	0.019643
306	1500	0.01	0.03	0.053079	-1.426580	0.043941	0.357673	0.019643
307	1500	0.02	0.01	0.097928	-1.373640	0.097398	0.369214	0.019643
308	1500	0.02	0.01	0.097177	-1.371340	0.107724	0.457644	0.019643
309	1500	0.02	0.01	0.079066	-1.393620	0.065257	0.363700	0.019643
310	1500	0.02	0.02	0.051787	-1.451360	0.052478	0.288154	0.019643
311	1500	0.02	0.02	0.063521	-1.455520	0.038440	0.315740	0.019643
312	1500	0.02	0.02	0.056099	-1.454000	0.031196	0.320155	0.019643
313	1500	0.02	0.03	0.095422	-1.371390	0.094583	0.377652	0.019643
314	1500	0.02	0.03	0.091832	-1.373460	0.085102	0.257390	0.019643
315	1500	0.02	0.03	0.100513	-1.357500	0.076860	0.484942	0.019643
316	1500	0.03	0.01	0.050500	-1.457110	0.042694	0.334805	0.019643
317	1500	0.03	0.01	0.047425	-1.458520	0.030773	0.320208	0.019643
318	1500	0.03	0.01	0.044942	-1.452230	0.023497	0.414095	0.019643
319	1500	0.03	0.02	0.040903	-1.469470	0.034692	0.237013	0.019643
320	1500	0.03	0.02	0.041299	-1.471180	0.020632	0.239029	0.019643
321	1500	0.03	0.02	0.040029	-1.461130	0.009002	0.454521	0.019643
322	1500	0.03	0.03	0.044123	-1.451280	0.044392	0.248262	0.019643
323	1500	0.03	0.03	0.044921	-1.449950	0.025663	0.199135	0.019643
324	1500	0.03	0.03	0.041603	-1.448130	0.013886	0.311295	0.019643

TEST DATA

Exp #	S	F	D	X	Y	Z	W	Tool Wear
1	500	0.01	0.01	0.103408	-1.430820	-0.015699	0.270185	0.001071
2	500	0.01	0.02	0.235751	-1.285750	0.237133	0.616138	0.001071
3	500	0.01	0.03	0.076789	-1.411080	0.039403	0.251949	0.001071
4	500	0.02	0.01	0.170515	-1.366040	0.141927	0.174760	0.001071
5	500	0.02	0.02	0.200056	-1.288690	0.187773	0.589756	0.001071
6	500	0.02	0.03	0.247586	-1.311110	0.268844	0.321340	0.001071
7	500	0.03	0.01	0.127092	-1.410120	0.109214	0.312770	0.001071
8	500	0.03	0.02	0.133569	-1.354480	0.105598	0.272689	0.001071
9	500	0.03	0.03	0.210960	-1.279870	0.237261	0.256727	0.001071
10	1000	0.01	0.01	0.167376	-1.321790	0.147443	0.452802	0.001071
11	1000	0.01	0.02	0.049992	-1.448490	-0.017632	0.241961	0.001071
12	1000	0.01	0.03	0.108134	-1.389200	0.062495	0.310213	0.001071
13	1000	0.02	0.01	0.113586	-1.421800	0.056752	0.281919	0.001071
14	1000	0.02	0.02	0.071487	-1.440050	-0.004799	0.322865	0.001071
15	1000	0.02	0.03	0.068075	-1.430540	0.023443	0.226214	0.001071
16	1000	0.03	0.01	0.099139	-1.375040	0.053323	0.299417	0.001071
17	1000	0.03	0.02	0.122677	-1.325910	0.061883	0.279658	0.001071
18	1000	0.03	0.03	0.120279	-1.349690	0.096196	0.371440	0.001071
19	1500	0.01	0.01	0.148157	-1.293570	0.092410	0.607875	0.001071
20	1500	0.01	0.02	0.062347	-1.434630	-0.006021	0.335853	0.001071
21	1500	0.01	0.03	0.058911	-1.439940	-0.013007	0.234790	0.001071
22	1500	0.02	0.01	0.082214	-1.399790	0.008395	0.195683	0.001071
23	1500	0.02	0.02	0.061900	-1.444340	-0.019831	0.206459	0.001071
24	1500	0.02	0.03	0.098103	-1.363160	0.018559	0.274516	0.001071
25	1500	0.03	0.01	0.055068	-1.441880	-0.010812	0.222817	0.001071

Exp #	S	F	D	X	Y	Z	W	Tool Wear
26	1500	0.03	0.02	0.048699	-1.441190	-0.018885	0.425353	0.001071
27	1500	0.03	0.03	0.045472	-1.446870	-0.028010	0.336833	0.001071
28	500	0.01	0.01	0.157653	-1.360240	0.109958	0.388926	0.003571
29	500	0.01	0.02	0.312557	-1.014820	0.225042	0.776312	0.003571
30	500	0.01	0.03	0.402947	-1.085880	0.389177	0.491272	0.003571
31	500	0.02	0.01	0.078818	-1.402400	0.040810	0.269807	0.003571
32	500	0.02	0.02	0.316836	-1.093630	0.274146	0.744495	0.003571
33	500	0.02	0.03	0.380662	-0.949184	0.365038	0.621417	0.003571
34	500	0.03	0.01	0.138932	-1.312830	0.103167	0.491345	0.003571
35	500	0.03	0.02	0.164012	-1.308930	0.083374	0.294990	0.003571
36	500	0.03	0.03	0.283327	-1.138160	0.185009	0.511798	0.003571
37	1000	0.01	0.01	0.055086	-1.434720	0.027233	0.286314	0.003571
38	1000	0.01	0.02	0.209076	-1.163180	0.220595	0.604607	0.003571
39	1000	0.01	0.03	0.144785	-1.301620	0.165560	0.441347	0.003571
40	1000	0.02	0.01	0.165041	-1.258760	0.146440	0.632799	0.003571
41	1000	0.02	0.02	0.094754	-1.385110	0.077946	0.453860	0.003571
42	1000	0.02	0.03	0.067176	-1.404550	0.043388	0.242044	0.003571
43	1000	0.03	0.01	0.126813	-1.334230	0.111111	0.297358	0.003571
44	1000	0.03	0.02	0.178965	-1.274100	0.153053	0.550548	0.003571
45	1000	0.03	0.03	0.113742	-1.338350	0.095795	0.293120	0.003571
46	1500	0.01	0.01	0.217801	-1.177760	0.234067	0.646128	0.003571
47	1500	0.01	0.02	0.075499	-1.420060	0.047443	0.307347	0.003571
48	1500	0.01	0.03	0.065546	-1.443970	0.028053	0.130060	0.003571
49	1500	0.02	0.01	0.084877	-1.399261	0.022930	0.216916	0.003571
50	1500	0.02	0.02	0.067586	-1.426220	0.029051	0.207792	0.003571
51	1500	0.02	0.03	0.104926	-1.363340	0.071226	0.355754	0.003571
52	1500	0.03	0.01	0.066417	-1.429250	0.035396	0.212281	0.003571
53	1500	0.03	0.02	0.057071	-1.432870	0.020671	0.497980	0.003571
54	1500	0.03	0.03	0.052607	-1.447260	0.016440	0.245869	0.003571
55	625	0.015	0.015	0.126559	-1.347390	0.131868	0.367391	0.007143
56	625	0.015	0.025	0.103143	-1.388570	0.074497	0.323327	0.007143
57	625	0.025	0.015	0.258450	1.778820	1.619050	0.508638	0.007143
58	625	0.025	0.025	0.149315	-1.279530	0.157199	0.426325	0.007143
59	875	0.015	0.015	0.234535	-1.295910	0.181497	0.334757	0.007143
60	875	0.015	0.025	0.100786	-1.387800	0.017358	0.230901	0.007143
61	875	0.025	0.015	0.140870	-1.324880	0.136395	0.312068	0.007143
62	875	0.025	0.025	0.129449	-1.339740	0.136529	0.587240	0.007143
63	500	0.01	0.01	0.108312	-1.417830	0.080285	0.418596	0.010714
64	500	0.01	0.02	0.225887	-1.253450	0.231218	0.806390	0.010714
65	500	0.01	0.03	0.224993	-1.241520	0.301518	0.511848	0.010714
66	500	0.02	0.01	0.184088	-1.405050	0.079995	0.249188	0.010714
67	500	0.02	0.02	0.172479	-1.317820	0.182005	0.690812	0.010714
68	500	0.02	0.03	0.204100	-1.273520	0.233981	0.497811	0.010714
69	500	0.03	0.01	0.093180	-1.418240	0.087789	0.205100	0.010714
70	500	0.03	0.02	0.128033	-1.374910	0.083434	0.209195	0.010714
71	500	0.03	0.03	0.180806	-1.341610	0.203903	0.292693	0.010714
72	1000	0.01	0.01	0.128829	-1.379780	0.062138	0.453797	0.010714
73	1000	0.01	0.02	0.117265	-1.405030	0.109288	0.436820	0.010714
74	1000	0.01	0.03	0.103470	-1.424130	0.088429	0.360564	0.010714
75	1000	0.02	0.01	0.103854	-1.478100	0.040029	0.466759	0.010714
76	1000	0.02	0.02	0.085926	-1.459210	0.057013	0.553203	0.010714

Exp #	S	F	D	X	Y	Z	W	Tool Wear
77	1000	0.02	0.03	0.070318	-1.491790	0.038097	0.232721	0.010714
78	1000	0.03	0.01	0.102783	-1.416990	0.088776	0.563824	0.010714
79	1000	0.03	0.02	0.142713	-1.365480	0.133663	0.389132	0.010714
80	1000	0.03	0.03	0.113709	-1.413190	0.091092	0.360840	0.010714
81	1500	0.01	0.01	0.137462	-1.340280	0.149639	0.690780	0.010714
82	1500	0.01	0.02	0.070942	-1.458360	0.040791	0.261485	0.010714
83	1500	0.01	0.03	0.052138	-1.472990	0.024538	0.165529	0.010714
84	1500	0.02	0.01	0.092484	-1.397750	0.064458	0.277581	0.010714
85	1500	0.02	0.02	0.093092	-1.428180	0.058081	0.314089	0.010714
86	1500	0.02	0.03	0.111385	-1.361570	0.081560	0.328902	0.010714
87	1500	0.03	0.01	0.089470	-1.430870	0.048435	0.200308	0.010714
88	1500	0.03	0.02	0.085949	-1.435370	0.039453	0.242652	0.010714
89	1500	0.03	0.03	0.051037	-1.459890	0.014510	0.374349	0.010714
90	625	0.015	0.015	0.184187	-1.266050	0.183979	0.566650	0.014286
91	625	0.015	0.025	0.185134	-1.265490	0.174830	0.776756	0.014286
92	625	0.025	0.015	0.354034	-1.014210	0.396077	0.940289	0.014286
93	625	0.025	0.025	0.229246	-1.141740	0.208565	0.805900	0.014286
94	875	0.015	0.015	0.234810	-0.870632	0.222833	0.573225	0.014286
95	875	0.015	0.025	0.135101	-1.338560	0.140170	0.393563	0.014286
96	875	0.025	0.015	0.178098	-1.268560	0.174297	0.586265	0.014286
97	875	0.025	0.025	0.166073	-1.268210	0.174403	1.038900	0.014286
98	500	0.01	0.01	0.105918	-1.351020	0.085072	0.485198	0.017857
99	500	0.01	0.02	0.202923	-1.215200	0.245550	0.623710	0.017857
100	500	0.01	0.03	0.262193	-1.192930	0.259660	0.568062	0.017857
101	500	0.02	0.01	0.163825	-1.386740	0.044065	0.353093	0.017857
102	500	0.02	0.02	0.173744	-1.373390	0.175438	0.838453	0.017857
103	500	0.02	0.03	0.203681	-1.259810	0.240622	0.493241	0.017857
104	500	0.03	0.01	0.109597	-1.504880	0.071961	0.438434	0.017857
105	500	0.03	0.02	0.126009	-1.430950	0.092082	0.164698	0.017857
106	500	0.03	0.03	0.063866	-1.411820	0.037199	0.325898	0.017857
107	1000	0.01	0.01	0.142443	-1.324910	0.133373	0.512099	0.017857
108	1000	0.01	0.02	0.126834	-1.415960	0.100192	0.461637	0.017857
109	1000	0.01	0.03	0.118178	-1.350230	0.096125	0.444508	0.017857
110	1000	0.02	0.01	0.146556	-1.357310	0.088418	0.441167	0.017857
111	1000	0.02	0.02	0.076054	-1.423670	0.052198	0.657973	0.017857
112	1000	0.02	0.03	0.090363	-1.421540	0.044081	0.227051	0.017857
113	1000	0.03	0.01	0.100466	-1.387280	0.072522	0.471116	0.017857
114	1000	0.03	0.02	0.117167	-1.339460	0.115133	0.373204	0.017857
115	1000	0.03	0.03	0.102663	-1.382140	0.082894	0.293951	0.017857
116	1500	0.01	0.01	0.157589	-1.291290	0.152023	0.656395	0.017857
117	1500	0.01	0.02	0.063453	-1.435760	0.032967	0.292016	0.017857
118	1500	0.01	0.03	0.055208	-1.446460	0.025334	0.215102	0.017857
119	1500	0.02	0.01	0.117071	-1.336020	0.112738	0.365672	0.017857
120	1500	0.02	0.02	0.056203	-1.453060	0.020237	0.232624	0.017857
121	1500	0.02	0.03	0.107004	-1.370960	0.072285	0.376459	0.017857
122	1500	0.03	0.01	0.055585	-1.457880	0.015246	0.276197	0.017857
123	1500	0.03	0.02	0.050537	-1.452760	0.014884	0.178972	0.017857
124	1500	0.03	0.03	0.047862	-1.437610	0.016674	0.297443	0.017857
125	500	0.01	0.01	0.100055	-1.470160	0.093468	0.686569	0.019643
126	500	0.01	0.02	0.209996	-1.218690	0.234267	0.740184	0.019643
127	500	0.01	0.03	0.263045	-1.225780	0.262741	0.488878	0.019643

Exp #	S	F	D	X	Y	Z	W	Tool Wear
128	500	0.02	0.01	0.136591	-1.382830	0.095073	0.174890	0.019643
129	500	0.02	0.02	0.202106	-1.316950	0.205890	0.764623	0.019643
130	500	0.02	0.03	0.263222	-1.203370	0.274163	0.639435	0.019643
131	500	0.03	0.01	0.093653	-1.433570	0.069762	0.237702	0.019643
132	500	0.03	0.02	0.130613	-1.365180	0.086148	0.216416	0.019643
133	500	0.03	0.03	0.169972	-1.281700	0.473717	0.344965	0.019643
134	1000	0.01	0.01	0.141437	-1.340220	0.107337	0.496698	0.019643
135	1000	0.01	0.02	0.136160	-1.405200	0.109900	0.537761	0.019643
136	1000	0.01	0.03	0.136509	-1.428260	0.085895	0.655720	0.019643
137	1000	0.02	0.01	0.164782	-1.384120	0.130099	0.527382	0.019643
138	1000	0.02	0.02	0.069074	-1.472770	0.040384	0.581718	0.019643
139	1000	0.02	0.03	0.083036	-1.434090	0.057638	0.213107	0.019643
140	1000	0.03	0.01	0.089061	-1.390360	0.071099	0.360255	0.019643
141	1000	0.03	0.02	0.129930	-1.301870	0.119924	0.703936	0.019643
142	1000	0.03	0.03	0.093309	-1.397360	0.072610	0.288930	0.019643
143	1500	0.01	0.01	0.145512	-1.284870	0.153674	0.824825	0.019643
144	1500	0.01	0.02	0.053089	-1.444680	0.026089	0.289323	0.019643
145	1500	0.01	0.03	0.050351	-1.422360	0.035597	0.614931	0.019643
146	1500	0.02	0.01	0.074912	-1.403550	0.056803	0.418429	0.019643
147	1500	0.02	0.02	0.048519	-1.455410	0.015859	0.361737	0.019643
148	1500	0.02	0.03	0.098481	-1.351090	0.073955	0.316378	0.019643
149	1500	0.03	0.01	0.045046	-1.440340	0.014226	0.309521	0.019643
150	1500	0.03	0.02	0.041082	-1.458570	0.005388	0.415361	0.019643
151	1500	0.03	0.03	0.039146	-1.459650	0.001581	0.272750	0.019643

S Spindle Speed
F Feed Rate
D Depth of Cut
X X direction vibration
Y Y direction vibration
Z Z direction vibration
W AE signal

APPENDIX C. MATLAB PROGRAM

main.m

```
clear all
echo off

% Set data format five digits science (0.00000E-000)
format short e

% Get filename and path using open Standard File Dialog Box
[filename, path] = uigetfile('*.xls','Pick an Excel File');

% Verify filename
if filename == 0
    disp('File not found')
else
    disp(['Congratulation! Following data has been loaded successfully!'])
    disp([path, filename])
    file = [path, filename];
end

% Read MS Excel file
xlsData = xlsread(file);

% plotting data for verification
x=xlsData(1:4096,1);
y=xlsData(1:4096,2);
z=xlsData(1:4096,3);
w=xlsData(1:4096,4);
t=[1:4096];
plot (t,x,t,y,t,z,t,w)
```

```
clear x;
clear y;
clear z;
clear w;
clear t;

% Devide data file into x,y,z,w data. Each data is devided into four groups, again
% x-direction vibration data group
x1=xlsData(1:1024,1);
x2=xlsData(1025:2048,1);
x3=xlsData(2049:3072,1);
x4=xlsData(3073:4096,1);

% y-direction vibration data group
y1=xlsData(1:1024,2);
y2=xlsData(1025:2048,2);
y3=xlsData(2049:3072,2);
y4=xlsData(3073:4096,2);

% z-direction vibration data group
z1=xlsData(1:1024,3);
z2=xlsData(1025:2048,3);
z3=xlsData(2049:3072,3);
z4=xlsData(3073:4096,3);

% w-sensor data group
w1=xlsData(1:1024,4);
w2=xlsData(1025:2048,4);
w3=xlsData(2049:3072,4);
w4=xlsData(3073:4096,4);

clear xlsData;
disp([' '])
disp(['Congratulation! Data grouping has been done successfully!'])
```

```
% Open output file
expfid = input('\nKey in output filename: ','s');
fid = fopen(expfid,'w');
disp(['Wavelet decomposition results will be stored in ',expfid])
disp([' '])

% Display signal directions and components names
disp(['ID    Component1    Component2    Component3    Component4
Component5    Component6'])

% Wavelet decomposition of x1
n=x1;
wavdec;

% Calculate satatistical characters of the component x1
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component x1
fprintf('x1 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'x1\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of x2
n=x2;
wavdec;

% Calculate satatistical characters of the component x2
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
```

```
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component x2
fprintf('x2 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'x2\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of x3
n=x3;
wavdec;

% Calculate satatistical characters of the component x3
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component x3
fprintf('x3 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'x3\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of x4
n=x4;
wavdec;
% Calculate satatistical characters of the component x4
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
```

```
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component x4
fprintf('x4 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'x4\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of y1
n=y1;
wavdec;

% Calculate satatistical characters of the component y1
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component y1
fprintf('y1 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'y1\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of y2
n=y2;
wavdec;

% Calculate satatistical characters of the component y2
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
```

```
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component y2
fprintf('y2 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'y2\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of y3
n=y3;
wavdec;

% Calculate satatistical characters of the component y3
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component y3
fprintf('y3 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'y3\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of y4
n=y4;
wavdec;

% Calculate satatistical characters of the component y4
```

```
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component y4
fprintf('y4 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'y4\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of z1
n=z1;
wavdec;

% Calculate satatistical characters of the component z1
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component z1
fprintf('z1%13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'z1\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of z2
n=z2;
wavdec;
```

```
% Calculate satatistical characters of the component z2
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component z2
fprintf('z2 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'z2\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of z3
n=z3;
wavdec;

% Calculate satatistical characters of the component z3
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component z3
fprintf('z3 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'z3\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of z4
n=z4;
wavdec;
```

```
% Calculate satatistical characters of the component z4
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component z4
fprintf('z4 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'z4\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of w1
n=w1;
wavdec;

% Calculate satatistical characters of the component w1
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component w1
fprintf('w1 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'w1\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of w2
n=w2;
```

```
wavdec;

% Calculate satatistical characters of the component w2
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component w2
fprintf('w2 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'w2\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of w3
n=w3;
wavdec;

% Calculate satatistical characters of the component w3
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component w3
fprintf('w3 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'w3\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

% Wavelet decomposition of w4
```

```
n=w4;
wavdec;

% Calculate satatistical characters of the component w4
stat_d1=mean(abs(d1-mean(d1)))+mean(d1);
stat_d2=mean(abs(d2-mean(d2)))+mean(d2);
stat_d3=mean(abs(d3-mean(d3)))+mean(d3);
stat_d4=mean(abs(d4-mean(d4)))+mean(d4);
stat_d5=mean(abs(d5-mean(d5)))+mean(d5);
stat_d6=mean(abs(d6-mean(d6)))+mean(d6);

% Write satatistical character of each component w4
fprintf('w4 %13.5e %13.5e %13.5e %13.5e %13.5e %13.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);
fprintf(fid,'w4\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e\t %12.5e
\n',stat_d1,stat_d2,stat_d3,stat_d4,stat_d5,stat_d6);

disp([' '])
disp(['Congratulation! All calculations have been done successfully!'])
disp([' '])

%Close output file
fclose(fid);
```

wavdec.m

```
[C,L]=wavedec(n,6,'db4');
d1=wrcoef('d',C,L,'db4',1);
d2=wrcoef('d',C,L,'db4',2);
d3=wrcoef('d',C,L,'db4',3);
d4=wrcoef('d',C,L,'db4',4);
d5=wrcoef('d',C,L,'db4',5);
d6=wrcoef('d',C,L,'db4',6);
clear C;
clear L;
```

divide.m

```
x1=xlsData(1:1024,1);
x2=xlsData(1025:2048,1);
x3=xlsData(2049:3072,1);
x4=xlsData(3073:4096,1);
y1=xlsData(1:1024,2);
y2=xlsData(1025:2048,2);
y3=xlsData(2049:3072,2);
y4=xlsData(3073:4096,2);
z1=xlsData(1:1024,3);
z2=xlsData(1025:2048,3);
z3=xlsData(2049:3072,3);
z4=xlsData(3073:4096,3);
w1=xlsData(1:1024,4);
w2=xlsData(1025:2048,4);
w3=xlsData(2049:3072,4);
w4=xlsData(3073:4096,4);
clear xlsData;
```

calorg.m

```
clear all
echo off

% Set data format five digits science (0.00000E-000)
format short e

% Get filename and path using open Standard File Dialog Box
[filename, path] = uigetfile('*.xls','Pick an Excel File');

% Verify filename
if filename == 0
    disp('File not found')
else
    disp(['Congratulation! Following data has been loaded successfully!'])
```

```
    disp([path, filename])
    file = [path, filename];
end

% Read MS Excel file
xlsData = xlsread(file);

% Devide data file into x,y,z,w data
% Each data is devided into four groups, again

% x-direction vibration data group
x1=xlsData(1:1024,1);
x2=xlsData(1025:2048,1);
x3=xlsData(2049:3072,1);
x4=xlsData(3073:4096,1);


% y-direction vibration data group
y1=xlsData(1:1024,2);
y2=xlsData(1025:2048,2);
y3=xlsData(2049:3072,2);
y4=xlsData(3073:4096,2);

% z-direction vibration data group
z1=xlsData(1:1024,3);
z2=xlsData(1025:2048,3);
z3=xlsData(2049:3072,3);
z4=xlsData(3073:4096,3);

% w-sensor data group
w1=xlsData(1:1024,4);
w2=xlsData(1025:2048,4);
w3=xlsData(2049:3072,4);
w4=xlsData(3073:4096,4);
```

```
clear xlsData;
disp([' '])
disp(['Congratulation! Data grouping has been done successfully!'])

stat_x1=mean(abs(x1-mean(x1)))+mean(x1);
stat_x2=mean(abs(x2-mean(x2)))+mean(x2);
stat_x3=mean(abs(x3-mean(x3)))+mean(x3);
stat_x4=mean(abs(x4-mean(x4)))+mean(x4);

stat_y1=mean(abs(y1-mean(y1)))+mean(y1);
stat_y2=mean(abs(y2-mean(y2)))+mean(y2);
stat_y3=mean(abs(y3-mean(y3)))+mean(y3);
stat_y4=mean(abs(y4-mean(y4)))+mean(y4);

stat_z1=mean(abs(z1-mean(z1)))+mean(z1);
stat_z2=mean(abs(z2-mean(z2)))+mean(z2);
stat_z3=mean(abs(z3-mean(z3)))+mean(z3);
stat_z4=mean(abs(z4-mean(z4)))+mean(z4);

stat_w1=mean(abs(w1-mean(w1)))+mean(w1);
stat_w2=mean(abs(w2-mean(w2)))+mean(w2);
stat_w3=mean(abs(w3-mean(w3)))+mean(w3);
stat_w4=mean(abs(w4-mean(w4)))+mean(w4);

disp([' '])
fprintf('%13.5e\n',stat_x1);
fprintf('%13.5e\n',stat_x2);
fprintf('%13.5e\n',stat_x3);
fprintf('%13.5e\n',stat_x4);
fprintf('%13.5e\n',stat_y1);
fprintf('%13.5e\n',stat_y2);
fprintf('%13.5e\n',stat_y3);
fprintf('%13.5e\n',stat_y4);
fprintf('%13.5e\n',stat_z1);
fprintf('%13.5e\n',stat_z2);
```

```
fprintf('%13.5e\n',stat_z3);
fprintf('%13.5e\n',stat_z4);
fprintf('%13.5e\n',stat_w1);
fprintf('%13.5e\n',stat_w2);
fprintf('%13.5e\n',stat_w3);
fprintf('%13.5e\n',stat_w4);
disp([' '])

expfid = input('\nKey in output filename: ','s');
fid = fopen(expfid,'a+');
disp(['Wavelet decomposition results will be stored in ',expfid])
disp([' '])

fprintf(fid,'%12.5e\n',stat_x1);
fprintf(fid,'%13.5e\n',stat_x2);
fprintf(fid,'%13.5e\n',stat_x3);
fprintf(fid,'%13.5e\n',stat_x4);
fprintf(fid,'%13.5e\n',stat_y1);
fprintf(fid,'%13.5e\n',stat_y2);
fprintf(fid,'%13.5e\n',stat_y3);
fprintf(fid,'%13.5e\n',stat_y4);
fprintf(fid,'%13.5e\n',stat_z1);
fprintf(fid,'%13.5e\n',stat_z2);
fprintf(fid,'%13.5e\n',stat_z3);
fprintf(fid,'%13.5e\n',stat_z4);
fprintf(fid,'%13.5e\n',stat_w1);
fprintf(fid,'%13.5e\n',stat_w2);
fprintf(fid,'%13.5e\n',stat_w3);
fprintf(fid,'%13.5e\n',stat_w4);
disp([' '])
disp([' '])
disp(['Congratulation! All calculations have been done successfully!'])
disp([' '])
%Close output file
fclose(fid);
```

calorg.m

```
clear all
echo off

% Set data format five digits science (0.00000E-000)
format short e

% Get filename and path using open Standard File Dialog Box
[filename, path] = uigetfile('*.xls','Pick an Excel File');

% Verify filename
if filename == 0
    disp('File not found')
else
    disp(['Congratulation! Following data has been loaded successfully!'])
    disp([path, filename])
    file = [path, filename];
end

% Read MS Excel file
xlsData = xlsread(file);

% Devide data file into x,y,z,w data
% Each data is devided into four groups, again

% x-direction vibration data group
x1=xlsData(1:1024,1);
x2=xlsData(1025:2048,1);
x3=xlsData(2049:3072,1);
x4=xlsData(3073:4096,1);

% y-direction vibration data group
y1=xlsData(1:1024,2);
```

```
y2=xlsData(1025:2048,2);
y3=xlsData(2049:3072,2);
y4=xlsData(3073:4096,2);

% z-direction vibration data group
z1=xlsData(1:1024,3);
z2=xlsData(1025:2048,3);
z3=xlsData(2049:3072,3);
z4=xlsData(3073:4096,3);

% w-sensor data group
w1=xlsData(1:1024,4);
w2=xlsData(1025:2048,4);
w3=xlsData(2049:3072,4);
w4=xlsData(3073:4096,4);

clear xlsData;
disp([' '])
disp(['Congratulation! Data grouping has been done successfully!'])

stat_x1=mean(abs(x1-mean(x1)))+mean(x1);
stat_x2=mean(abs(x2-mean(x2)))+mean(x2);
stat_x3=mean(abs(x3-mean(x3)))+mean(x3);
stat_x4=mean(abs(x4-mean(x4)))+mean(x4);

stat_y1=mean(abs(y1-mean(y1)))+mean(y1);
stat_y2=mean(abs(y2-mean(y2)))+mean(y2);
stat_y3=mean(abs(y3-mean(y3)))+mean(y3);
stat_y4=mean(abs(y4-mean(y4)))+mean(y4);

stat_z1=mean(abs(z1-mean(z1)))+mean(z1);
stat_z2=mean(abs(z2-mean(z2)))+mean(z2);
stat_z3=mean(abs(z3-mean(z3)))+mean(z3);
stat_z4=mean(abs(z4-mean(z4)))+mean(z4);
```

```
stat_w1=mean(abs(w1-mean(w1)))+mean(w1);
stat_w2=mean(abs(w2-mean(w2)))+mean(w2);
stat_w3=mean(abs(w3-mean(w3)))+mean(w3);
stat_w4=mean(abs(w4-mean(w4)))+mean(w4);

disp([' '])
fprintf('%13.5e\n',stat_x1);
fprintf('%13.5e\n',stat_x2);
fprintf('%13.5e\n',stat_x3);
fprintf('%13.5e\n',stat_x4);
fprintf('%13.5e\n',stat_y1);
fprintf('%13.5e\n',stat_y2);
fprintf('%13.5e\n',stat_y3);
fprintf('%13.5e\n',stat_y4);
fprintf('%13.5e\n',stat_z1);
fprintf('%13.5e\n',stat_z2);
fprintf('%13.5e\n',stat_z3);
fprintf('%13.5e\n',stat_z4);
fprintf('%13.5e\n',stat_w1);
fprintf('%13.5e\n',stat_w2);
fprintf('%13.5e\n',stat_w3);
fprintf('%13.5e\n',stat_w4);
disp([' '])

expfid = input('\nKey in output filename: ','s');
fid = fopen(expfid,'a+');
disp(['Wavelet decomposition results will be stored in ',expfid])
disp([' '])

fprintf(fid,'%12.5e\n',stat_x1);
fprintf(fid,'%13.5e\n',stat_x2);
fprintf(fid,'%13.5e\n',stat_x3);
fprintf(fid,'%13.5e\n',stat_x4);
fprintf(fid,'%13.5e\n',stat_y1);
fprintf(fid,'%13.5e\n',stat_y2);
```

```
fprintf(fid,'%13.5e\n',stat_y3);
fprintf(fid,'%13.5e\n',stat_y4);
fprintf(fid,'%13.5e\n',stat_z1);
fprintf(fid,'%13.5e\n',stat_z2);
fprintf(fid,'%13.5e\n',stat_z3);
fprintf(fid,'%13.5e\n',stat_z4);
fprintf(fid,'%13.5e\n',stat_w1);
fprintf(fid,'%13.5e\n',stat_w2);
fprintf(fid,'%13.5e\n',stat_w3);
fprintf(fid,'%13.5e\n',stat_w4);
disp([' '])

disp([' '])
disp(['Congratulation! All calculations have been done successfully!'])
disp([' '])

%Close output file
fclose(fid);
```

APPENDIX D. DATA WITH TRANSFORMED SIGNAL DATA

TRAIN DATA

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
1	500	0.01	0.01	0.001746	-0.016448	-0.001016	-0.106407	0.010714
2	500	0.01	0.01	-0.005053	-0.005545	-0.003981	-0.095368	0.010714
3	500	0.01	0.01	0.005539	-0.005004	0.001849	-0.139619	0.010714
4	500	0.01	0.02	0.010370	0.015960	0.012454	-0.156339	0.010714
5	500	0.01	0.02	0.017062	0.042440	0.008443	-0.094517	0.010714
6	500	0.01	0.02	0.001475	0.012474	0.009922	-0.061977	0.010714
7	500	0.01	0.03	0.009187	0.021762	0.012292	0.081183	0.010714
8	500	0.01	0.03	0.011050	0.001810	-0.004095	-0.063284	0.010714
9	500	0.01	0.03	-0.003591	0.007514	0.011384	0.181995	0.010714
10	500	0.02	0.01	0.004217	-0.002671	0.004942	-0.247749	0.010714
11	500	0.02	0.01	0.008430	-0.001234	0.000075	-0.245536	0.010714
12	500	0.02	0.01	0.004415	0.000952	0.018046	-0.186563	0.010714
13	500	0.02	0.02	-0.005273	0.015923	0.015433	0.351156	0.010714
14	500	0.02	0.02	0.006159	-0.000287	0.003264	0.268775	0.010714
15	500	0.02	0.02	0.003282	0.011753	0.004899	0.196752	0.010714
16	500	0.02	0.03	0.006037	0.001596	-0.000394	0.157921	0.010714
17	500	0.02	0.03	0.013508	0.005822	0.013014	0.091431	0.010714
18	500	0.02	0.03	0.003302	0.000544	0.013675	0.120121	0.010714
19	500	0.03	0.01	0.006037	0.001596	-0.000394	-0.143716	0.010714
20	500	0.03	0.01	0.013508	0.005822	0.013014	-0.101674	0.010714
21	500	0.03	0.01	0.003302	0.000544	0.013675	-0.047367	0.010714
22	500	0.03	0.02	0.004648	-0.007323	0.002140	-0.026120	0.010714
23	500	0.03	0.02	0.007511	-0.002012	-0.002728	-0.060016	0.010714
24	500	0.03	0.02	0.005095	-0.013232	-0.000031	-0.113899	0.010714
25	500	0.03	0.03	0.001742	0.005137	0.004709	-0.054005	0.010714
26	500	0.03	0.03	0.001613	0.014009	0.007845	0.071130	0.010714
27	500	0.03	0.03	0.005384	-0.000974	0.001445	0.062241	0.010714
28	1000	0.01	0.01	0.001828	0.011217	0.005266	0.115329	0.010714
29	1000	0.01	0.01	-0.001730	0.006901	0.004021	0.052612	0.010714
30	1000	0.01	0.01	0.004518	0.008220	0.006413	-0.039745	0.010714
31	1000	0.01	0.02	0.004871	0.002275	0.003054	-0.077168	0.010714
32	1000	0.01	0.02	0.005210	0.004050	0.006198	0.018348	0.010714
33	1000	0.01	0.02	-0.000894	0.008035	0.015497	0.019624	0.010714
34	1000	0.01	0.03	0.003195	0.000577	-0.000931	-0.135519	0.010714
35	1000	0.01	0.03	0.005255	-0.006675	-0.002523	-0.168302	0.010714
36	1000	0.01	0.03	-0.001569	0.005797	0.000157	-0.198891	0.010714
37	1000	0.02	0.01	-0.001127	0.002807	0.000556	-0.178102	0.010714
38	1000	0.02	0.01	0.002841	-0.003778	0.001367	-0.025788	0.010714
39	1000	0.02	0.01	0.007182	-0.002352	-0.000279	-0.124979	0.010714
40	1000	0.02	0.02	0.001361	-0.005783	0.000775	-0.015013	0.010714
41	1000	0.02	0.02	-0.001197	-0.001458	0.002392	0.008601	0.010714
42	1000	0.02	0.02	0.000774	-0.003339	-0.000174	-0.035596	0.010714
43	1000	0.02	0.03	0.000651	-0.003378	-0.000080	-0.219011	0.010714

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
44	1000	0.02	0.03	0.002178	-0.008991	-0.001643	-0.183973	0.010714
45	1000	0.02	0.03	0.003031	-0.005241	-0.002063	-0.224797	0.010714
46	1000	0.03	0.01	0.002111	0.011066	-0.009586	0.046890	0.010714
47	1000	0.03	0.01	0.004426	-0.000467	-0.006238	0.194211	0.010714
48	1000	0.03	0.01	0.006277	-0.003563	-0.000437	0.055968	0.010714
49	1000	0.03	0.02	-0.003492	0.010193	0.008300	0.011162	0.010714
50	1000	0.03	0.02	-0.000326	0.014568	0.007019	0.089367	0.010714
51	1000	0.03	0.02	0.007105	-0.002553	0.006461	0.090642	0.010714
52	1000	0.03	0.03	0.001304	-0.007685	-0.000335	0.043517	0.010714
53	1000	0.03	0.03	0.004376	-0.001340	-0.003525	0.134346	0.010714
54	1000	0.03	0.03	0.001934	0.004266	-0.000890	0.105116	0.010714
55	1500	0.01	0.01	0.005093	0.008001	0.002607	0.148331	0.010714
56	1500	0.01	0.01	0.001826	0.014723	0.010834	0.319210	0.010714
57	1500	0.01	0.01	0.002373	0.011070	0.009296	0.317320	0.010714
58	1500	0.01	0.02	0.000986	0.000718	0.002301	-0.153433	0.010714
59	1500	0.01	0.02	0.000598	-0.001815	0.001809	-0.098713	0.010714
60	1500	0.01	0.02	0.004162	-0.000856	0.005209	-0.131014	0.010714
61	1500	0.01	0.03	-0.001613	-0.005282	-0.001495	-0.229186	0.010714
62	1500	0.01	0.03	-0.002029	-0.002329	-0.004136	-0.230180	0.010714
63	1500	0.01	0.03	-0.002087	-0.002720	-0.001283	-0.252405	0.010714
64	1500	0.02	0.01	-0.005433	0.003507	-0.000338	-0.080581	0.010714
65	1500	0.02	0.01	-0.001712	-0.001203	-0.000998	0.000994	0.010714
66	1500	0.02	0.01	0.000603	0.001949	0.001279	-0.078874	0.010714
67	1500	0.02	0.02	0.038590	0.038001	0.034930	-0.060077	0.010714
68	1500	0.02	0.02	0.034511	0.039251	0.035923	-0.096213	0.010714
69	1500	0.02	0.02	0.035056	0.032279	0.033020	-0.137069	0.010714
70	1500	0.02	0.03	0.036004	0.039038	0.039946	0.000871	0.010714
71	1500	0.02	0.03	0.040132	0.041255	0.032641	0.094485	0.010714
72	1500	0.02	0.03	0.040784	0.033856	0.033927	-0.069893	0.010714
73	1500	0.03	0.01	0.035435	0.035528	0.036793	-0.057144	0.010714
74	1500	0.03	0.01	0.039096	0.033164	0.035985	-0.061340	0.010714
75	1500	0.03	0.01	0.034697	0.035597	0.035464	-0.048298	0.010714
76	1500	0.03	0.02	0.036777	0.039098	0.034310	-0.036791	0.010714
77	1500	0.03	0.02	0.035283	0.035137	0.035140	-0.098323	0.010714
78	1500	0.03	0.02	0.034997	0.035428	0.035526	-0.090431	0.010714
79	1500	0.03	0.03	-0.001760	-0.006559	-0.003534	-0.060080	0.010714
80	1500	0.03	0.03	-0.000998	-0.004380	-0.002001	0.009319	0.010714
81	1500	0.03	0.03	-0.003058	-0.005279	-0.002088	0.033756	0.010714
82	500	0.01	0.01	-0.010791	-0.017063	-0.010806	-0.136583	0.017857
83	500	0.01	0.01	-0.013003	-0.022546	-0.009549	-0.167662	0.017857
84	500	0.01	0.01	-0.014954	-0.025086	-0.013786	-0.150415	0.017857
85	500	0.01	0.02	0.013427	0.032081	-0.001046	0.093661	0.017857
86	500	0.01	0.02	0.001783	0.010361	0.007289	-0.091909	0.017857
87	500	0.01	0.02	0.008782	0.017160	0.018620	-0.026209	0.017857
88	500	0.01	0.03	0.002560	0.006563	0.002353	0.164942	0.017857
89	500	0.01	0.03	-0.001241	0.008331	-0.000483	0.040924	0.017857
90	500	0.01	0.03	0.002884	0.009574	0.009259	0.033546	0.017857

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
91	500	0.02	0.01	0.001199	0.000815	0.000293	-0.199279	0.017857
92	500	0.02	0.01	0.012903	0.011327	0.006254	-0.257118	0.017857
93	500	0.02	0.01	-0.001032	0.002727	-0.000551	-0.183417	0.017857
94	500	0.02	0.02	-0.000355	-0.009386	-0.003998	0.389769	0.017857
95	500	0.02	0.02	0.002055	-0.012017	0.002598	0.343873	0.017857
96	500	0.02	0.02	-0.004389	-0.003250	0.003343	0.416938	0.017857
97	500	0.02	0.03	0.006271	0.016099	0.006642	0.134411	0.017857
98	500	0.02	0.03	0.001611	0.035456	0.017831	0.081813	0.017857
99	500	0.02	0.03	0.001073	0.015532	0.008581	0.142210	0.017857
100	500	0.03	0.01	-0.001893	-0.012018	-0.005146	-0.102796	0.017857
101	500	0.03	0.01	-0.001488	-0.008543	-0.012597	-0.065189	0.017857
102	500	0.03	0.01	-0.004017	-0.012853	-0.003423	0.044654	0.017857
103	500	0.03	0.02	-0.005867	0.000226	-0.007475	-0.115978	0.017857
104	500	0.03	0.02	-0.000339	0.000766	-0.004592	-0.137362	0.017857
105	500	0.03	0.02	0.005795	0.000875	0.002117	-0.152284	0.017857
106	500	0.03	0.03	-0.014079	-0.020177	-0.017824	0.059559	0.017857
107	500	0.03	0.03	-0.014059	-0.021358	-0.017139	0.041175	0.017857
108	500	0.03	0.03	-0.015773	-0.021340	-0.019851	0.039329	0.017857
109	1000	0.01	0.01	-0.006323	0.000805	-0.000708	-0.010737	0.017857
110	1000	0.01	0.01	-0.002076	0.002319	-0.000641	0.041877	0.017857
111	1000	0.01	0.01	-0.006249	-0.003450	-0.003713	0.081883	0.017857
112	1000	0.01	0.02	-0.003399	-0.003398	0.005203	-0.053273	0.017857
113	1000	0.01	0.02	0.000086	-0.004769	-0.006465	-0.043593	0.017857
114	1000	0.01	0.02	-0.001918	0.012532	0.003679	-0.017988	0.017857
115	1000	0.01	0.03	-0.000180	-0.013434	-0.001414	-0.051309	0.017857
116	1000	0.01	0.03	-0.003772	-0.011698	-0.002312	-0.151380	0.017857
117	1000	0.01	0.03	-0.003863	-0.008205	-0.002245	-0.039336	0.017857
118	1000	0.02	0.01	-0.005907	0.007989	-0.003300	0.047236	0.017857
119	1000	0.02	0.01	-0.000290	-0.005958	-0.002222	-0.055751	0.017857
120	1000	0.02	0.01	-0.008050	0.006067	0.000549	0.089610	0.017857
121	1000	0.02	0.02	-0.002399	-0.012326	-0.009702	-0.010854	0.017857
122	1000	0.02	0.02	-0.002264	-0.015931	-0.004835	0.188655	0.017857
123	1000	0.02	0.02	-0.007432	-0.006600	-0.006590	0.009916	0.017857
124	1000	0.02	0.03	-0.007578	-0.006985	-0.002923	-0.247366	0.017857
125	1000	0.02	0.03	-0.000593	-0.011772	-0.006468	-0.173185	0.017857
126	1000	0.02	0.03	-0.002508	-0.012807	-0.008738	-0.178476	0.017857
127	1000	0.03	0.01	-0.006481	-0.002718	-0.004100	-0.014799	0.017857
128	1000	0.03	0.01	-0.004613	0.003586	-0.001258	0.003241	0.017857
129	1000	0.03	0.01	0.000591	0.004156	-0.001404	0.082077	0.017857
130	1000	0.03	0.02	-0.004779	-0.003499	-0.003592	-0.000724	0.017857
131	1000	0.03	0.02	0.001248	-0.005399	-0.006376	-0.009266	0.017857
132	1000	0.03	0.02	-0.006936	-0.003039	-0.007282	-0.035551	0.017857
133	1000	0.03	0.03	0.000107	0.000106	-0.001440	-0.041463	0.017857
134	1000	0.03	0.03	-0.003831	0.001166	-0.003228	0.039682	0.017857
135	1000	0.03	0.03	-0.005303	-0.011648	-0.004581	-0.040637	0.017857
136	1500	0.01	0.01	0.001458	-0.004458	0.006253	0.464840	0.017857
137	1500	0.01	0.01	0.002141	0.014264	-0.000741	0.351914	0.017857

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
138	1500	0.01	0.01	0.005142	-0.001107	-0.004183	0.319397	0.017857
139	1500	0.01	0.02	-0.002528	-0.001116	-0.002483	-0.146262	0.017857
140	1500	0.01	0.02	-0.000511	-0.004444	-0.003636	-0.055512	0.017857
141	1500	0.01	0.02	-0.001623	-0.007673	0.000065	-0.172639	0.017857
142	1500	0.01	0.03	-0.001050	0.000057	-0.001412	-0.215458	0.017857
143	1500	0.01	0.03	-0.000310	-0.003167	0.000233	-0.141554	0.017857
144	1500	0.01	0.03	-0.002072	-0.003907	-0.001227	-0.210059	0.017857
145	1500	0.02	0.01	0.001370	-0.000678	-0.001301	-0.073308	0.017857
146	1500	0.02	0.01	0.001662	-0.000906	0.001499	-0.034659	0.017857
147	1500	0.02	0.01	0.000590	0.002647	0.001845	0.058166	0.017857
148	1500	0.02	0.02	-0.003173	-0.003650	-0.003932	-0.117690	0.017857
149	1500	0.02	0.02	-0.000439	-0.003288	-0.002048	0.162873	0.017857
150	1500	0.02	0.02	-0.002998	-0.003612	-0.001742	-0.044874	0.017857
151	1500	0.02	0.03	0.002266	0.003048	-0.000151	-0.065327	0.017857
152	1500	0.02	0.03	0.000961	0.002497	-0.000699	-0.090030	0.017857
153	1500	0.02	0.03	-0.000557	0.001890	0.001888	0.036335	0.017857
154	1500	0.03	0.01	-0.001693	-0.005704	-0.003379	0.044460	0.017857
155	1500	0.03	0.01	-0.001448	-0.006369	-0.003934	0.036015	0.017857
156	1500	0.03	0.01	-0.003202	-0.003457	-0.001998	0.089245	0.017857
157	1500	0.03	0.02	-0.002859	-0.006047	-0.004051	-0.038138	0.017857
158	1500	0.03	0.02	-0.002308	-0.002775	-0.002265	-0.055054	0.017857
159	1500	0.03	0.02	-0.002668	-0.006280	-0.003741	-0.075534	0.017857
160	1500	0.03	0.03	-0.004283	-0.005089	-0.003145	-0.033644	0.017857
161	1500	0.03	0.03	-0.005170	-0.004190	-0.003215	-0.008761	0.017857
162	1500	0.03	0.03	-0.004241	-0.008766	-0.004603	-0.071431	0.017857
163	500	0.01	0.01	-0.013983	-0.022206	-0.014540	-0.031642	0.019643
164	500	0.01	0.01	-0.007773	-0.009182	-0.000949	-0.070210	0.019643
165	500	0.01	0.01	-0.011549	-0.023365	-0.015347	-0.046453	0.019643
166	500	0.01	0.02	0.010730	0.007701	0.016625	-0.100098	0.019643
167	500	0.01	0.02	0.018768	0.025561	0.010816	-0.033062	0.019643
168	500	0.01	0.02	0.011573	0.002089	0.009734	0.121537	0.019643
169	500	0.01	0.03	0.002513	-0.002115	0.004356	0.143090	0.019643
170	500	0.01	0.03	-0.001474	0.003540	0.004321	0.176863	0.019643
171	500	0.01	0.03	0.000087	0.009448	0.002008	0.052492	0.019643
172	500	0.02	0.01	0.003717	0.012309	0.004935	-0.245401	0.019643
173	500	0.02	0.01	0.001772	-0.004233	-0.000054	-0.245646	0.019643
174	500	0.02	0.01	-0.000731	0.002082	-0.004202	-0.270002	0.019643
175	500	0.02	0.02	-0.002903	-0.005669	-0.005753	0.283739	0.019643
176	500	0.02	0.02	-0.005439	0.009536	-0.003379	0.347000	0.019643
177	500	0.02	0.02	-0.000549	-0.002096	0.002722	0.283811	0.019643
178	500	0.02	0.03	0.010241	0.021773	0.003378	0.103774	0.019643
179	500	0.02	0.03	0.003417	0.027617	0.014641	0.101587	0.019643
180	500	0.02	0.03	0.003811	0.024858	0.008368	0.216136	0.019643
181	500	0.03	0.01	-0.006235	-0.017672	-0.010466	-0.088438	0.019643
182	500	0.03	0.01	-0.001520	-0.018836	-0.010678	-0.136623	0.019643
183	500	0.03	0.01	-0.005155	-0.011438	-0.005941	-0.104891	0.019643
184	500	0.03	0.02	-0.005754	-0.014240	-0.009269	-0.073469	0.019643

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
185	500	0.03	0.02	-0.005103	-0.011346	-0.008553	-0.139995	0.019643
186	500	0.03	0.02	-0.005919	-0.009927	-0.001957	-0.081219	0.019643
187	500	0.03	0.03	-0.003959	0.002892	0.001013	0.056284	0.019643
188	500	0.03	0.03	-0.005969	-0.005152	-0.006012	-0.022389	0.019643
189	500	0.03	0.03	-0.001807	0.023830	0.003408	0.044372	0.019643
190	1000	0.01	0.01	-0.002482	0.002238	-0.003795	-0.000372	0.019643
191	1000	0.01	0.01	-0.007669	-0.002291	0.000514	0.108966	0.019643
192	1000	0.01	0.01	0.000293	0.018236	-0.000004	0.101969	0.019643
193	1000	0.01	0.02	0.004739	0.002447	-0.004141	0.037680	0.019643
194	1000	0.01	0.02	-0.001277	-0.004884	-0.001221	0.037755	0.019643
195	1000	0.01	0.02	0.005147	-0.006460	-0.006732	0.038149	0.019643
196	1000	0.01	0.03	-0.005655	-0.007501	-0.006785	-0.054898	0.019643
197	1000	0.01	0.03	-0.002185	-0.009522	-0.005440	-0.061782	0.019643
198	1000	0.01	0.03	-0.003879	-0.009413	-0.009257	-0.068971	0.019643
199	1000	0.02	0.01	-0.005982	-0.005266	-0.005919	-0.131257	0.019643
200	1000	0.02	0.01	0.000142	-0.004977	-0.010086	0.003683	0.019643
201	1000	0.02	0.01	-0.002561	-0.005010	-0.004585	0.278468	0.019643
202	1000	0.02	0.02	-0.003527	-0.006859	0.001282	0.180390	0.019643
203	1000	0.02	0.02	-0.005082	0.000283	0.000018	0.319969	0.019643
204	1000	0.02	0.02	-0.002930	0.000157	-0.001137	0.299659	0.019643
205	1000	0.02	0.03	0.000846	-0.007053	-0.005212	-0.201078	0.019643
206	1000	0.02	0.03	0.000103	0.000330	-0.007212	-0.197539	0.019643
207	1000	0.02	0.03	0.000100	-0.008503	-0.002822	-0.160209	0.019643
208	1000	0.03	0.01	-0.010390	-0.016330	-0.008933	0.080839	0.019643
209	1000	0.03	0.01	-0.010379	-0.009997	-0.010703	-0.023242	0.019643
210	1000	0.03	0.01	-0.013165	-0.017181	-0.014153	0.118227	0.019643
211	1000	0.03	0.02	-0.012181	-0.003755	-0.007912	0.070859	0.019643
212	1000	0.03	0.02	-0.008345	-0.006472	-0.007033	0.061273	0.019643
213	1000	0.03	0.02	-0.006419	-0.000257	-0.009062	0.213622	0.019643
214	1000	0.03	0.03	-0.008146	-0.006434	-0.009025	-0.057475	0.019643
215	1000	0.03	0.03	-0.011680	-0.016972	-0.014631	0.001754	0.019643
216	1000	0.03	0.03	-0.009971	-0.014897	-0.010725	-0.004354	0.019643
217	1500	0.01	0.01	-0.006209	-0.001255	-0.005741	0.457350	0.019643
218	1500	0.01	0.01	-0.008672	0.002264	-0.000347	0.416651	0.019643
219	1500	0.01	0.01	-0.005638	0.004945	-0.004583	0.493991	0.019643
220	1500	0.01	0.02	-0.013323	-0.010361	-0.012861	-0.178823	0.019643
221	1500	0.01	0.02	-0.013254	-0.012245	-0.012547	-0.113040	0.019643
222	1500	0.01	0.02	-0.012669	-0.010665	-0.011885	-0.134142	0.019643
223	1500	0.01	0.03	-0.013120	-0.010638	-0.010924	-0.118979	0.019643
224	1500	0.01	0.03	-0.009006	-0.001552	-0.007627	0.006154	0.019643
225	1500	0.01	0.03	-0.013253	-0.009349	-0.010399	-0.039344	0.019643
226	1500	0.02	0.01	-0.008440	-0.002549	-0.007138	0.035764	0.019643
227	1500	0.02	0.01	-0.010706	-0.006701	-0.006186	0.124194	0.019643
228	1500	0.02	0.01	-0.009458	-0.006522	-0.006700	0.030250	0.019643
229	1500	0.02	0.02	-0.014000	-0.013664	-0.013912	-0.045296	0.019643
230	1500	0.02	0.02	-0.013062	-0.014378	-0.014246	-0.017710	0.019643
231	1500	0.02	0.02	-0.012270	-0.013917	-0.013241	-0.013295	0.019643

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
232	1500	0.02	0.03	-0.011167	-0.008262	-0.011550	0.044202	0.019643
233	1500	0.02	0.03	-0.009917	-0.007729	-0.006634	-0.076060	0.019643
234	1500	0.02	0.03	-0.009441	-0.001030	-0.006538	0.151492	0.019643
235	1500	0.03	0.01	-0.015210	-0.014662	-0.014475	0.064922	0.019643
236	1500	0.03	0.01	-0.014560	-0.014717	-0.014285	0.050325	0.019643
237	1500	0.03	0.01	-0.015768	-0.017154	-0.014585	0.144212	0.019643
238	1500	0.03	0.02	-0.016197	-0.019216	-0.016150	-0.032870	0.019643
239	1500	0.03	0.02	-0.015885	-0.018906	-0.015123	-0.030854	0.019643
240	1500	0.03	0.02	-0.015733	-0.017794	-0.015210	0.184638	0.019643
241	1500	0.03	0.03	-0.015595	-0.017479	-0.014299	-0.021621	0.019643
242	1500	0.03	0.03	-0.014736	-0.015457	-0.012274	-0.070748	0.019643
243	1500	0.03	0.03	-0.014904	-0.016969	-0.013483	0.041412	0.019643

TEST DATA

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
1	500	0.01	0.01	-0.006031	-0.018323	-0.009388	-0.193965	0.001071
2	500	0.01	0.02	0.002192	0.003909	-0.003601	0.037479	0.001071
3	500	0.01	0.03	-0.008996	-0.023687	-0.015140	-0.441219	0.001071
4	500	0.02	0.01	0.004360	0.012556	-0.004545	-0.193343	0.001071
5	500	0.02	0.02	0.003163	0.004068	-0.005484	0.133992	0.001071
6	500	0.02	0.03	0.008150	-0.005925	-0.004255	-0.222085	0.001071
7	500	0.03	0.01	-0.000459	-0.004405	-0.011308	0.040714	0.001071
8	500	0.03	0.02	-0.004462	-0.007844	-0.004258	-0.060180	0.001071
9	500	0.03	0.03	0.008702	0.009166	-0.003657	-0.136955	0.001071
10	1000	0.01	0.01	0.006070	0.007253	0.000625	-0.093049	0.001071
11	1000	0.01	0.02	-0.004775	-0.010855	-0.004179	-0.245877	0.001071
12	1000	0.01	0.03	-0.002849	-0.001073	-0.004931	-0.119613	0.001071
13	1000	0.02	0.01	-0.006276	-0.001050	-0.005624	-0.128268	0.001071
14	1000	0.02	0.02	-0.003709	-0.009683	-0.007745	-0.071742	0.001071
15	1000	0.02	0.03	-0.002104	-0.008061	-0.005579	-0.152813	0.001071
16	1000	0.03	0.01	0.000063	-0.001375	-0.000800	0.024893	0.001071
17	1000	0.03	0.02	-0.001187	-0.001942	0.000442	-0.021718	0.001071
18	1000	0.03	0.03	0.001161	0.003453	0.001431	0.043211	0.001071
19	1500	0.01	0.01	0.012191	0.005506	-0.000853	-0.019676	0.001071
20	1500	0.01	0.02	0.001502	0.004334	0.001160	-0.061164	0.001071
21	1500	0.01	0.03	0.002326	0.006030	0.002000	0.068307	0.001071
22	1500	0.02	0.01	0.001122	-0.002910	-0.003308	-0.256589	0.001071
23	1500	0.02	0.02	0.003974	-0.001986	-0.002360	-0.126991	0.001071
24	1500	0.02	0.03	0.005145	0.006347	0.003050	0.059887	0.001071
25	1500	0.03	0.01	-0.005304	-0.008501	-0.003725	-0.054175	0.001071
26	1500	0.03	0.02	-0.001582	-0.001250	-0.001643	0.155470	0.001071
27	1500	0.03	0.03	-0.000376	-0.000365	0.000596	0.074058	0.001071
28	500	0.01	0.01	-0.005477	0.006836	-0.000326	-0.075224	0.003571
29	500	0.01	0.02	0.037421	0.056657	0.024293	0.197653	0.003571
30	500	0.01	0.03	0.033329	0.024536	0.010225	-0.201896	0.003571
31	500	0.02	0.01	0.000089	-0.005535	-0.006393	-0.098296	0.003571
32	500	0.02	0.02	0.009504	0.030025	0.041564	0.288731	0.003571

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
33	500	0.02	0.03	0.020655	0.090600	0.034188	0.077992	0.003571
34	500	0.03	0.01	0.003542	-0.001356	0.007078	0.219289	0.003571
35	500	0.03	0.02	0.002937	0.001958	0.000381	-0.037879	0.003571
36	500	0.03	0.03	0.025167	0.039901	0.024577	0.118116	0.003571
37	1000	0.01	0.01	-0.001011	-0.006546	-0.004084	-0.259537	0.003571
38	1000	0.01	0.02	0.003701	0.016653	0.005850	0.116769	0.003571
39	1000	0.01	0.03	0.000004	0.007546	-0.000605	0.011521	0.003571
40	1000	0.02	0.01	0.015126	-0.006379	0.004630	0.222612	0.003571
41	1000	0.02	0.02	0.000120	0.002850	-0.003451	0.059253	0.003571
42	1000	0.02	0.03	-0.002138	-0.001464	-0.001230	-0.136983	0.003571
43	1000	0.03	0.01	0.001068	0.015235	0.002572	0.022834	0.003571
44	1000	0.03	0.02	0.006813	0.008437	0.004154	0.249172	0.003571
45	1000	0.03	0.03	0.004526	-0.001233	-0.000461	-0.035109	0.003571
46	1500	0.01	0.01	0.012290	0.022541	0.019682	0.018577	0.003571
47	1500	0.01	0.02	0.004412	0.001844	0.002201	-0.089670	0.003571
48	1500	0.01	0.03	0.003184	0.004957	0.004175	-0.036423	0.003571
49	1500	0.02	0.01	-0.000266	-0.002005	-0.002458	-0.235356	0.003571
50	1500	0.02	0.02	0.003764	-0.001542	0.001472	-0.125658	0.003571
51	1500	0.02	0.03	0.004450	0.007033	0.007521	0.141125	0.003571
52	1500	0.03	0.01	-0.001231	-0.003494	-0.003276	-0.064711	0.003571
53	1500	0.03	0.02	-0.001666	-0.002277	0.000886	0.228097	0.003571
54	1500	0.03	0.03	0.002307	-0.000351	-0.000086	-0.016906	0.003571
55	625	0.015	0.015	-0.004870	-0.009007	-0.003855	-0.097516	0.007143
56	625	0.015	0.025	-0.013607	-0.020717	-0.015294	-0.208195	0.007143
57	625	0.025	0.015	0.007839	0.104410	0.011168	0.154446	0.007143
58	625	0.025	0.025	-0.008450	-0.009051	0.002815	0.015046	0.007143
59	875	0.015	0.015	-0.000701	0.002406	-0.001009	-0.126626	0.007143
60	875	0.015	0.025	-0.005110	-0.009678	-0.008664	-0.228156	0.007143
61	875	0.025	0.015	0.006677	0.005487	-0.007283	-0.036112	0.007143
62	875	0.025	0.025	0.000959	-0.008600	0.000974	0.216274	0.007143
63	500	0.01	0.01	0.000601	-0.008459	-0.006015	-0.045554	0.010714
64	500	0.01	0.02	0.003456	-0.008425	0.005590	0.227731	0.010714
65	500	0.01	0.03	0.006416	-0.014129	-0.011071	-0.181320	0.010714
66	500	0.02	0.01	0.009505	0.015373	0.003682	-0.118915	0.010714
67	500	0.02	0.02	0.006206	-0.000384	0.010198	0.235048	0.010714
68	500	0.02	0.03	0.009795	0.012479	0.012734	-0.045614	0.010714
69	500	0.03	0.01	0.011340	0.024370	0.018317	-0.066956	0.010714
70	500	0.03	0.02	0.003852	-0.001995	0.001633	-0.123674	0.010714
71	500	0.03	0.03	0.003408	0.003902	0.008705	-0.100989	0.010714
72	1000	0.01	0.01	0.003159	0.010009	0.003190	-0.092054	0.010714
73	1000	0.01	0.02	0.006167	0.001930	0.000402	-0.051018	0.010714
74	1000	0.01	0.03	-0.000097	-0.006854	-0.001665	-0.069262	0.010714
75	1000	0.02	0.01	0.001858	-0.006792	0.001962	0.056572	0.010714
76	1000	0.02	0.02	0.002407	-0.002201	0.002813	0.158596	0.010714
77	1000	0.02	0.03	-0.002011	0.000782	0.000244	-0.146306	0.010714
78	1000	0.03	0.01	0.004306	-0.000870	0.001869	0.289300	0.010714
79	1000	0.03	0.02	0.004905	0.005485	-0.000423	0.087756	0.010714

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
80	1000	0.03	0.03	0.007184	-0.000852	-0.000225	0.032611	0.010714
81	1500	0.01	0.01	0.005532	0.011568	0.006323	0.063229	0.010714
82	1500	0.01	0.02	0.004736	0.001145	0.001852	-0.135532	0.010714
83	1500	0.01	0.03	-0.000016	0.002288	-0.000255	-0.000954	0.010714
84	1500	0.02	0.01	-0.004231	0.000582	-0.000027	-0.174691	0.010714
85	1500	0.02	0.02	0.035652	0.034673	0.039131	-0.019361	0.010714
86	1500	0.02	0.03	0.035308	0.045577	0.041268	0.114273	0.010714
87	1500	0.03	0.01	0.031702	0.036755	0.030904	-0.076684	0.010714
88	1500	0.03	0.02	0.036848	0.038502	0.034223	-0.027231	0.010714
89	1500	0.03	0.03	-0.001427	-0.001815	-0.001442	0.111574	0.010714
90	625	0.015	0.015	-0.005111	-0.007950	-0.001887	0.101743	0.014286
91	625	0.015	0.025	-0.009735	-0.012126	0.000233	0.245234	0.014286
92	625	0.025	0.015	0.024521	0.039830	0.017235	0.586097	0.014286
93	625	0.025	0.025	0.008363	0.003023	0.021849	0.394621	0.014286
94	875	0.015	0.015	0.001125	0.012336	-0.000988	0.111842	0.014286
95	875	0.015	0.025	-0.002348	-0.003252	0.005347	-0.065494	0.014286
96	875	0.025	0.015	-0.000691	0.009646	0.002333	0.238085	0.014286
97	875	0.025	0.025	0.008136	-0.001615	-0.001750	0.667934	0.014286
98	500	0.01	0.01	-0.008471	-0.013668	-0.009263	0.021048	0.017857
99	500	0.01	0.02	0.014684	0.005873	-0.002700	0.045051	0.017857
100	500	0.01	0.03	-0.003272	0.001565	0.001268	-0.125106	0.017857
101	500	0.02	0.01	0.003075	0.014749	-0.000440	-0.015010	0.017857
102	500	0.02	0.02	0.001372	-0.006767	0.002811	0.382689	0.017857
103	500	0.02	0.03	-0.001031	-0.008115	0.000357	-0.050184	0.017857
104	500	0.03	0.01	-0.002088	-0.006999	0.002273	0.166378	0.017857
105	500	0.03	0.02	-0.000016	-0.001503	0.004249	-0.168171	0.017857
106	500	0.03	0.03	-0.009908	-0.019406	-0.016953	-0.067784	0.017857
107	1000	0.01	0.01	-0.003043	0.005489	0.001514	-0.033752	0.017857
108	1000	0.01	0.02	0.000890	-0.009521	-0.003717	-0.026201	0.017857
109	1000	0.01	0.03	-0.013393	-0.011195	-0.008360	0.014682	0.017857
110	1000	0.02	0.01	-0.000792	-0.000285	-0.002387	0.030980	0.017857
111	1000	0.02	0.02	-0.002538	-0.006266	-0.005964	0.263366	0.017857
112	1000	0.02	0.03	-0.000033	-0.009446	-0.006591	-0.151976	0.017857
113	1000	0.03	0.01	-0.002510	0.000608	-0.003075	0.196592	0.017857
114	1000	0.03	0.02	-0.003543	-0.002007	-0.002839	0.071828	0.017857
115	1000	0.03	0.03	-0.001361	-0.002134	0.002570	-0.034278	0.017857
116	1500	0.01	0.01	0.004633	0.020064	0.007653	0.028844	0.017857
117	1500	0.01	0.02	-0.000253	-0.001711	-0.001614	-0.105001	0.017857
118	1500	0.01	0.03	-0.002270	0.003448	0.001821	0.048619	0.017857
119	1500	0.02	0.01	0.002117	-0.001565	-0.003529	-0.086600	0.017857
120	1500	0.02	0.02	-0.000898	-0.007078	-0.003749	-0.100826	0.017857
121	1500	0.02	0.03	-0.001670	0.008595	0.004006	0.161830	0.017857
122	1500	0.03	0.01	-0.006283	-0.008744	-0.006803	-0.000795	0.017857
123	1500	0.03	0.02	-0.004750	-0.006516	-0.003979	-0.090911	0.017857
124	1500	0.03	0.03	-0.003384	0.002163	-0.002549	0.034668	0.017857
125	500	0.01	0.01	-0.008842	-0.016750	-0.010236	0.222419	0.019643
126	500	0.01	0.02	0.000975	0.026918	0.005958	0.161525	0.019643

Exp #	S	F	D	X'	Y'	Z'	W'	Tool Wear
127	500	0.01	0.03	-0.005535	0.005578	-0.002902	-0.204290	0.019643
128	500	0.02	0.01	0.008875	0.009162	0.001490	-0.193213	0.019643
129	500	0.02	0.02	-0.004371	-0.014632	-0.001791	0.308859	0.019643
130	500	0.02	0.03	0.006264	0.005994	-0.004532	0.096010	0.019643
131	500	0.03	0.01	-0.005734	-0.013856	-0.003104	-0.034354	0.019643
132	500	0.03	0.02	-0.002873	-0.000117	-0.004141	-0.116453	0.019643
133	500	0.03	0.03	-0.002566	-0.005353	0.003803	-0.048717	0.019643
134	1000	0.01	0.01	0.000689	-0.005605	0.004796	-0.049153	0.019643
135	1000	0.01	0.02	-0.000980	-0.012073	0.002056	0.049923	0.019643
136	1000	0.01	0.03	0.002354	0.018992	-0.001369	0.225894	0.019643
137	1000	0.02	0.01	0.007430	-0.005953	-0.004457	0.117195	0.019643
138	1000	0.02	0.02	-0.004857	-0.009438	-0.006748	0.187111	0.019643
139	1000	0.02	0.03	0.000542	-0.001259	-0.003951	-0.165920	0.019643
140	1000	0.03	0.01	-0.012256	-0.015854	-0.012993	0.085731	0.019643
141	1000	0.03	0.02	-0.004265	0.003162	-0.003504	0.402560	0.019643
142	1000	0.03	0.03	-0.009597	-0.010542	-0.011151	-0.039299	0.019643
143	1500	0.01	0.01	0.002950	0.001652	0.012122	0.197274	0.019643
144	1500	0.01	0.02	-0.011173	-0.012376	-0.009366	-0.107694	0.019643
145	1500	0.01	0.03	-0.011430	-0.004460	-0.005797	0.448448	0.019643
146	1500	0.02	0.01	-0.009726	-0.011538	-0.011004	-0.033843	0.019643
147	1500	0.02	0.02	-0.014506	-0.016574	-0.012797	0.028287	0.019643
148	1500	0.02	0.03	-0.012006	-0.001537	-0.004794	0.101749	0.019643
149	1500	0.03	0.01	-0.018822	-0.018257	-0.016947	0.032529	0.019643
150	1500	0.03	0.02	-0.016826	-0.018562	-0.016654	0.145478	0.019643
151	1500	0.03	0.03	-0.015550	-0.013879	-0.014851	0.009975	0.019643

X' Transformed x direction vibration
Y' Transformed y direction vibration
Z' Transformed z direction vibration
W' Transformed AE signal

APPENDIX E. COEFFICIENT VALUES OF MODEL WITH RAW DATA

Term	Coefficient value
Intercept	14.2087256
spindle	-0.0114245
feed	-769.42958
depth	-145.79851
x	-154.9072
y	9.92152157
z	-15.595899
w	-44.786007
spindle*feed	0.42013651
spindle*depth	0.3856035
spindle*x	0.16465582
spindle*y	-0.0080753
spindle*z	-0.0045143
spindle*w	0.03681936
feed*depth	6598.90055
feed*x	7364.42812
feed*y	-548.59429
feed*z	2718.68767
feed*w	2202.03451
depth*x	5191.62517
depth*y	-91.124372
depth*z	-1681.8627
depth*w	769.126848
x*y	-111.50245
x*z	705.696606
x*w	444.754867
y*z	-11.106839
y*w	-30.96549
z*w	108.744978
spindle*feed*depth	-7.1203428
spindle*feed*x	-5.7739093
spindle*feed*y	0.30587251

Term	Coefficient value
spindle*feed*z	1.16133893
spindle*feed*w	-1.3208016
spindle*depth*x	-8.7606021
spindle*depth*z	0.09041605
spindle*depth*w	-1.3816324
spindle*x*y	0.11945252
spindle*x*z	-0.7997324
spindle*x*w	-0.442784
spindle*y*z	-0.0019526
spindle*y*w	0.02560073
spindle*z*w	-0.0508742
feed*depth*x	-215699.52
feed*depth*y	4534.10558
feed*depth*z	56384.4003
feed*depth*w	-24784.374
feed*x*y	5359.79315
feed*x*z	-40217.755
feed*x*w	-19634.301
feed*y*z	2020.25493
feed*y*w	1546.00837
feed*z*w	-8005.0355
depth*x*y	3790.8934
depth*x*z	-30156.993
depth*x*w	-17582.699
depth*y*z	-1285.4496
depth*y*w	493.437865
depth*z*w	2400.07422
x*y*z	521.241724
x*y*w	319.319789
x*z*w	-1957.0987
y*z*w	72.0270529
spindle*feed*depth*x	278.646745
spindle*feed*depth*y	-5.2363215
spindle*feed*depth*z	-125.98361
spindle*feed*depth*w	30.0495736

Term	Coefficient value
spindle*feed*x*y	-4.278282
spindle*feed*x*z	18.8980678
spindle*feed*x*w	14.6952825
spindle*feed*y*z	0.67900088
spindle*feed*y*w	-0.9363911
spindle*feed*z*w	-1.7369102
spindle*depth*x*y	-6.3701379
spindle*depth*x*z	58.6817742
spindle*depth*x*w	25.9002208
spindle*depth*y*z	0.06568817
spindle*depth*y*w	-0.9483744
spindle*depth*z*w	1.38922226
spindle*x*y*z	-0.6006802
spindle*x*y*w	-0.3197829
spindle*x*z*w	1.96971332
spindle*y*z*w	-0.0340893
feed*depth*x*y	-160819.4
feed*depth*x*z	1217842.16
feed*depth*x*w	672199.306
feed*depth*y*z	40300.5477
feed*depth*y*w	-16137.657
feed*depth*z*w	-176373.46
feed*x*y*z	-30120.494
feed*x*y*w	-14240.898
feed*x*z*w	90538.4384
feed*y*z*w	-5634.2554
depth*x*y*z	-22324.843
depth*x*y*w	-12824.737
depth*x*z*w	86900.477
depth*y*z*w	2258.62296
x*y*z*w	-1423.4473
spindle*feed*depth*x*y	207.792257
spindle*feed*depth*x*z	-1217.6217
spindle*feed*depth*x*w	-821.73643
spindle*feed*depth*y*z	-85.557404

Term	Coefficient value
spindle*feed*depth*y*w	20.9265577
spindle*feed*depth*z*w	345.093837
spindle*feed*x*y*z	15.5783483
spindle*feed*x*y*w	10.8581642
spindle*feed*x*z*w	-27.537193
spindle*feed*y*z*w	-1.1192862
spindle*depth*x*y*z	43.3553525
spindle*depth*x*y*w	18.8165767
spindle*depth*x*z*w	-150.44007
spindle*depth*y*z*w	0.71040575
spindle*x*y*z*w	1.45916119
feed*depth*x*y*z	935293.136
feed*depth*x*y*w	499988.533
feed*depth*x*z*w	-2676623.7
feed*depth*y*z*w	-143286.65
feed*x*y*z*w	67282.9249
depth*x*y*z*w	63246.3784
spindle*feed*depth*x*y*z	-970.99689
spindle*feed*depth*x*y*w	-611.77674
spindle*feed*depth*x*z*w	2352.70869
spindle*feed*depth*y*z*w	249.181588
spindle*feed*x*y*z*w	-24.059376
spindle*depth*x*y*z*w	-110.3277
feed*depth*x*y*z*w	-2035021
spindle*feed*depth*x*y*z*w	1907.8076

APPENDIX F. COEFFICIENT VALUES OF MODEL WITH SIGNIFICANT COMPONENTS

Term	Coefficient
Intercept	0.01084999
spindle	-0.0000363
feed	-20.034067
depth	24.7213627
x	-23.647979
y	5.75152916
z	-22.457361
w	-0.3847428
spindle*feed	0.01552384
spindle*depth	-0.014687
spindle*x	0.01531902
spindle*y	-0.0079458
spindle*z	0.03131759
spindle*w	0.00050945
feed*depth	61.1211777
feed*x	1432.52616
feed*y	288.792112
feed*z	2443.40218
feed*w	64.4676862
depth*x	60.2869901
depth*y	-1043.2775
depth*z	-3.5528485
depth*w	-27.485213
x*y	252.797529
x*z	2168.42345
x*w	52.148312
y*z	512.749787
y*w	-5.4697614
z*w	98.4994674
spindle*feed*depth	-0.1494169
spindle*feed*x	-0.6446314
spindle*feed*y	0.07623676
spindle*feed*z	-2.645722
spindle*feed*w	-0.0540171

Term	Coefficient value
spindle*depth*x	-0.2512514
spindle*depth*y	1.08111587
spindle*depth*z	-0.8628368
spindle*depth*w	0.00465461
spindle*x*y	0.26863917
spindle*x*z	-2.3173236
spindle*x*w	-0.0417898
spindle*y*z	-0.6959787
spindle*y*w	0.0111057
spindle*z*w	-0.1220457
feed*depth*x	-26222.153
feed*depth*y	12808.9146
feed*depth*z	-78010.786
feed*depth*w	-1488.6308
feed*x*y	-18536.167
feed*x*z	-147986.05
feed*x*w	-2920.4116
feed*y*z	-56353.877
feed*y*w	-982.91491
feed*z*w	-7951.4045
depth*x*y	17004.777
depth*x*z	-61718.702
depth*x*w	-662.745
depth*y*z	11417.9217
depth*y*w	2001.13899
depth*z*w	-3401.8437
x*y*z	-48746.425
x*y*w	-214.68315
x*z*w	-6482.9606
y*z*w	-2307.3386
spindle*feed*depth*x	13.7610408
spindle*feed*depth*y	-28.712445
spindle*feed*depth*z	106.283184
spindle*feed*depth*w	1.61675127
spindle*feed*x*y	-18.889067
spindle*feed*x*z	139.421047
spindle*feed*x*w	1.34743655

Term	Coefficient value
spindle*feed*y*z	55.1284119
spindle*feed*y*w	0.0119716
spindle*feed*z*w	8.65835063
spindle*depth*x*y	-33.571686
spindle*depth*x*z	98.548656
spindle*depth*x*w	1.51708224
spindle*depth*y*z	2.45480291
spindle*depth*y*w	-2.282665
spindle*depth*z*w	5.72560118
spindle*x*y*z	46.024961
spindle*x*y*w	-0.5562167
spindle*x*z*w	7.16220594
spindle*y*z*w	2.7137636
feed*depth*x*y	-206321.16
feed*depth*x*z	5479165.28
feed*depth*x*w	72804.0677
feed*depth*y*z	1437061.44
feed*depth*y*w	-10554.573
feed*depth*z*w	343581.521
feed*x*y*z	3290995.43
feed*x*y*w	11039.1304
feed*x*z*w	412651.936
feed*y*z*w	186526.442
depth*x*y*z	1072887.42
depth*x*y*w	-52777.684
depth*x*z*w	271341.571
depth*y*z*w	46407.9305
x*y*z*w	142941.617
spindle*feed*depth*x*y	1746.14063
spindle*feed*depth*x*z	-6502.0321
spindle*feed*depth*x*w	-55.027582
spindle*feed*depth*y*z	-1614.0427
spindle*feed*depth*y*w	62.6287261
spindle*feed*depth*z*w	-427.29285
spindle*feed*x*y*z	-2671.6443
spindle*feed*x*y*w	63.6855415
spindle*feed*x*z*w	-409.62618

Term	Coefficient value
spindle*feed*y*z*w	-182.51193
spindle*depth*x*y*z	-1446.0975
spindle*depth*x*y*w	78.4283894
spindle*depth*x*z*w	-386.63537
spindle*depth*y*z*w	-78.137696
spindle*x*y*z*w	-152.45747
feed*depth*x*y*z	-111018775
feed*depth*x*y*w	1616717.27
feed*depth*x*z*w	-18785547
feed*depth*y*z*w	-6871688.4
feed*x*y*z*w	-8933526.8
depth*x*y*z*w	-4870237.2
spindle*feed*depth*x*y*z	104440.732
spindle*feed*depth*x*y*w	-5038.2011
spindle*feed*depth*x*z*w	22508.1594
spindle*feed*depth*y*z*w	7179.79499
spindle*feed*x*y*z*w	8111.72248
spindle*depth*x*y*z*w	6588.44797
feed*depth*x*y*z*w	367154275
spindle*feed*depth*x*y*z*w	-383730.89

APPENDIX G. TEST RESULT OF REGRESSION MODEL

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
1	500	0.01	0.01	0.103408	-1.430820	-0.015699	0.270185	0.0010714	SHARP	SHARP
2	500	0.01	0.02	0.235751	-1.285750	0.237133	0.616138	0.0010714	SHARP	SHARP
3	500	0.01	0.03	0.076789	-1.411080	0.039403	0.251949	0.0010714	SHARP	SHARP
4	500	0.02	0.01	0.170515	-1.366040	0.141927	0.174760	0.0010714	SHARP	SHARP
5	500	0.02	0.02	0.200056	-1.288690	0.187773	0.589756	0.0010714	SHARP	SHARP
6	500	0.02	0.03	0.247586	-1.311110	0.268844	0.321340	0.0010714	SHARP	SHARP
7	500	0.03	0.01	0.127092	-1.410120	0.109214	0.312770	0.0010714	SHARP	SHARP
8	500	0.03	0.02	0.133569	-1.354480	0.105598	0.272689	0.0010714	SHARP	SHARP
9	500	0.03	0.03	0.210960	-1.279870	0.237261	0.256727	0.0010714	SHARP	SHARP
10	1000	0.01	0.01	0.167376	-1.321790	0.147443	0.452802	0.0010714	SHARP	SHARP
11	1000	0.01	0.02	0.049992	-1.448490	-0.017632	0.241961	0.0010714	SHARP	SHARP
12	1000	0.01	0.03	0.108134	-1.389200	0.062495	0.310213	0.0010714	SHARP	SHARP
13	1000	0.02	0.01	0.113586	-1.421800	0.056752	0.281919	0.0010714	SHARP	SHARP
14	1000	0.02	0.02	0.071487	-1.440050	-0.004799	0.322865	0.0010714	**SHARP**	**WORN**
15	1000	0.02	0.03	0.068075	-1.430540	0.023443	0.226214	0.0010714	**SHARP**	**WORN**
16	1000	0.03	0.01	0.099139	-1.375040	0.053323	0.299417	0.0010714	SHARP	SHARP
17	1000	0.03	0.02	0.122677	-1.325910	0.061883	0.279658	0.0010714	SHARP	SHARP
18	1000	0.03	0.03	0.120279	-1.349690	0.096196	0.371440	0.0010714	SHARP	SHARP
19	1500	0.01	0.01	0.148157	-1.293570	0.092410	0.607875	0.0010714	SHARP	SHARP
20	1500	0.01	0.02	0.062347	-1.434630	-0.006021	0.335853	0.0010714	SHARP	SHARP
21	1500	0.01	0.03	0.058911	-1.439940	-0.013007	0.234790	0.0010714	SHARP	SHARP
22	1500	0.02	0.01	0.082214	-1.399790	0.008395	0.195683	0.0010714	SHARP	SHARP
23	1500	0.02	0.02	0.061900	-1.444340	-0.019831	0.206459	0.0010714	SHARP	SHARP
24	1500	0.02	0.03	0.098103	-1.363160	0.018559	0.274516	0.0010714	SHARP	SHARP
25	1500	0.03	0.01	0.055068	-1.441880	-0.010812	0.222817	0.0010714	SHARP	SHARP
26	1500	0.03	0.02	0.048699	-1.441190	-0.018885	0.425353	0.0010714	SHARP	SHARP
27	1500	0.03	0.03	0.045472	-1.446870	-0.028010	0.336833	0.0010714	SHARP	SHARP
28	500	0.01	0.01	0.157653	-1.360240	0.109958	0.388926	0.0035714	SHARP	SHARP
29	500	0.01	0.02	0.312557	-1.014820	0.225042	0.776312	0.0035714	SHARP	SHARP
30	500	0.01	0.03	0.402947	-1.085880	0.389177	0.491272	0.0035714	SHARP	SHARP
31	500	0.02	0.01	0.078818	-1.402400	0.040810	0.269807	0.0035714	SHARP	SHARP
32	500	0.02	0.02	0.316836	-1.093630	0.274146	0.744495	0.0035714	SHARP	SHARP
33	500	0.02	0.03	0.380662	-0.949184	0.365038	0.621417	0.0035714	SHARP	SHARP
34	500	0.03	0.01	0.138932	-1.312830	0.103167	0.491345	0.0035714	SHARP	SHARP
35	500	0.03	0.02	0.164012	-1.308930	0.083374	0.294990	0.0035714	SHARP	SHARP
36	500	0.03	0.03	0.283327	-1.138160	0.185009	0.511798	0.0035714	SHARP	SHARP
37	1000	0.01	0.01	0.055086	-1.434720	0.027233	0.286314	0.0035714	SHARP	SHARP
38	1000	0.01	0.02	0.209076	-1.163180	0.220595	0.604607	0.0035714	SHARP	SHARP
39	1000	0.01	0.03	0.144785	-1.301620	0.165560	0.441347	0.0035714	SHARP	SHARP
40	1000	0.02	0.01	0.165041	-1.258760	0.146440	0.632799	0.0035714	SHARP	SHARP
41	1000	0.02	0.02	0.094754	-1.385110	0.077946	0.453860	0.0035714	**SHARP**	**WORN**
42	1000	0.02	0.03	0.067176	-1.404550	0.043388	0.242044	0.0035714	**SHARP**	**WORN**
43	1000	0.03	0.01	0.126813	-1.334230	0.111111	0.297358	0.0035714	SHARP	SHARP
44	1000	0.03	0.02	0.178965	-1.274100	0.153053	0.550548	0.0035714	SHARP	SHARP

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
45	1000	0.03	0.03	0.113742	-1.338350	0.095795	0.293120	0.0035714	**SHARP**	**WORN**
46	1500	0.01	0.01	0.217801	-1.177760	0.234067	0.646128	0.0035714	SHARP	SHARP
47	1500	0.01	0.02	0.075499	-1.420060	0.047443	0.307347	0.0035714	**SHARP**	**WORN**
48	1500	0.01	0.03	0.065546	-1.443970	0.028053	0.130060	0.0035714	SHARP	SHARP
49	1500	0.02	0.01	0.084877	-1.399261	0.022930	0.216916	0.0035714	SHARP	SHARP
50	1500	0.02	0.02	0.067586	-1.426220	0.029051	0.207792	0.0035714	SHARP	SHARP
51	1500	0.02	0.03	0.104926	-1.363340	0.071226	0.355754	0.0035714	SHARP	SHARP
52	1500	0.03	0.01	0.066417	-1.429250	0.035396	0.212281	0.0035714	SHARP	SHARP
53	1500	0.03	0.02	0.057071	-1.432870	0.020671	0.497980	0.0035714	SHARP	SHARP
54	1500	0.03	0.03	0.052607	-1.447260	0.016440	0.245869	0.0035714	SHARP	SHARP
55	625	0.015	0.015	0.126559	-1.347390	0.131868	0.367391	0.0071429	SHARP	SHARP
56	625	0.015	0.025	0.103143	-1.388570	0.074497	0.323327	0.0071429	**SHARP**	**WORN**
57	625	0.025	0.015	0.258450	1.778820	1.619050	0.508638	0.0071429	SHARP	SHARP
58	625	0.025	0.025	0.149315	-1.279530	0.157199	0.426325	0.0071429	**SHARP**	**WORN**
59	875	0.015	0.015	0.234535	-1.295910	0.181497	0.334757	0.0071429	SHARP	SHARP
60	875	0.015	0.025	0.100786	-1.387800	0.017358	0.230901	0.0071429	SHARP	SHARP
61	875	0.025	0.015	0.140870	-1.324880	0.136395	0.312068	0.0071429	**SHARP**	**WORN**
62	875	0.025	0.025	0.129449	-1.339740	0.136529	0.587240	0.0071429	**SHARP**	**WORN**
63	500	0.01	0.01	0.108312	-1.417830	0.080285	0.418596	0.0107143	WORN	WORN
64	500	0.01	0.02	0.225887	-1.253450	0.231218	0.806390	0.0107143	WORN	WORN
65	500	0.01	0.03	0.224993	-1.241520	0.301518	0.511848	0.0107143	WORN	WORN
66	500	0.02	0.01	0.184088	-1.405050	0.079995	0.249188	0.0107143	WORN	WORN
67	500	0.02	0.02	0.172479	-1.317820	0.182005	0.690812	0.0107143	WORN	WORN
68	500	0.02	0.03	0.204100	-1.273520	0.233981	0.497811	0.0107143	WORN	WORN
69	500	0.03	0.01	0.093180	-1.418240	0.087789	0.205100	0.0107143	WORN	WORN
70	500	0.03	0.02	0.128033	-1.374910	0.083434	0.209195	0.0107143	WORN	WORN
71	500	0.03	0.03	0.180806	-1.341610	0.203903	0.292693	0.0107143	WORN	WORN
72	1000	0.01	0.01	0.128829	-1.379780	0.062138	0.453797	0.0107143	**WORN**	**SHARP**
73	1000	0.01	0.02	0.117265	-1.405030	0.109288	0.436820	0.0107143	WORN	WORN
74	1000	0.01	0.03	0.103470	-1.424130	0.088429	0.360564	0.0107143	**WORN**	**SHARP**
75	1000	0.02	0.01	0.103854	-1.478100	0.040029	0.466759	0.0107143	**WORN**	**SHARP**
76	1000	0.02	0.02	0.085926	-1.459210	0.057013	0.553203	0.0107143	WORN	WORN
77	1000	0.02	0.03	0.070318	-1.491790	0.038097	0.232721	0.0107143	WORN	WORN
78	1000	0.03	0.01	0.102783	-1.416990	0.088776	0.563824	0.0107143	WORN	WORN
79	1000	0.03	0.02	0.142713	-1.365480	0.133663	0.389132	0.0107143	**WORN**	**SHARP**
80	1000	0.03	0.03	0.113709	-1.413190	0.091092	0.360840	0.0107143	WORN	WORN
81	1500	0.01	0.01	0.137462	-1.340280	0.149639	0.690780	0.0107143	WORN	WORN
82	1500	0.01	0.02	0.070942	-1.458360	0.040791	0.261485	0.0107143	**WORN**	**SHARP**
83	1500	0.01	0.03	0.052138	-1.472990	0.024538	0.165529	0.0107143	WORN	WORN
84	1500	0.02	0.01	0.092484	-1.397750	0.064458	0.277581	0.0107143	WORN	WORN
85	1500	0.02	0.02	0.093092	-1.428180	0.058081	0.314089	0.0107143	WORN	WORN
86	1500	0.02	0.03	0.111385	-1.361570	0.081560	0.328902	0.0107143	WORN	WORN
87	1500	0.03	0.01	0.089470	-1.430870	0.048435	0.200308	0.0107143	WORN	WORN
88	1500	0.03	0.02	0.085949	-1.435370	0.039453	0.242652	0.0107143	WORN	WORN
89	1500	0.03	0.03	0.051037	-1.459890	0.014510	0.374349	0.0107143	WORN	WORN
90	625	0.015	0.015	0.184187	-1.266050	0.183979	0.566650	0.0142857	WORN	WORN
91	625	0.015	0.025	0.185134	-1.265490	0.174830	0.776756	0.0142857	WORN	WORN

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
92	625	0.025	0.015	0.354034	-1.014210	0.396077	0.940289	0.0142857	WORN	WORN
93	625	0.025	0.025	0.229246	-1.141740	0.208565	0.805900	0.0142857	WORN	WORN
94	875	0.015	0.015	0.234810	-0.870632	0.222833	0.573225	0.0142857	WORN	WORN
95	875	0.015	0.025	0.135101	-1.338560	0.140170	0.393563	0.0142857	WORN	WORN
96	875	0.025	0.015	0.178098	-1.268560	0.174297	0.586265	0.0142857	WORN	WORN
97	875	0.025	0.025	0.166073	-1.268210	0.174403	1.038900	0.0142857	WORN	WORN
98	500	0.01	0.01	0.105918	-1.351020	0.085072	0.485198	0.0178571	WORN	WORN
99	500	0.01	0.02	0.202923	-1.215200	0.245550	0.623710	0.0178571	WORN	WORN
100	500	0.01	0.03	0.262193	-1.192930	0.259660	0.568062	0.0178571	WORN	WORN
101	500	0.02	0.01	0.163825	-1.386740	0.044065	0.353093	0.0178571	WORN	WORN
102	500	0.02	0.02	0.173744	-1.373390	0.175438	0.838453	0.0178571	WORN	WORN
103	500	0.02	0.03	0.203681	-1.259810	0.240622	0.493241	0.0178571	WORN	WORN
104	500	0.03	0.01	0.109597	-1.504880	0.071961	0.438434	0.0178571	WORN	WORN
105	500	0.03	0.02	0.126009	-1.430950	0.092082	0.164698	0.0178571	WORN	WORN
106	500	0.03	0.03	0.063866	-1.411820	0.037199	0.325898	0.0178571	WORN	WORN
107	1000	0.01	0.01	0.142443	-1.324910	0.133373	0.512099	0.0178571	WORN	WORN
108	1000	0.01	0.02	0.126834	-1.415960	0.100192	0.461637	0.0178571	WORN	WORN
109	1000	0.01	0.03	0.118178	-1.350230	0.096125	0.444508	0.0178571	WORN	WORN
110	1000	0.02	0.01	0.146556	-1.357310	0.088418	0.441167	0.0178571	WORN	WORN
111	1000	0.02	0.02	0.076054	-1.423670	0.052198	0.657973	0.0178571	WORN	WORN
112	1000	0.02	0.03	0.090363	-1.421540	0.044081	0.227051	0.0178571	WORN	WORN
113	1000	0.03	0.01	0.100466	-1.387280	0.072522	0.471116	0.0178571	WORN	WORN
114	1000	0.03	0.02	0.117167	-1.339460	0.115133	0.373204	0.0178571	WORN	WORN
115	1000	0.03	0.03	0.102663	-1.382140	0.082894	0.293951	0.0178571	WORN	WORN
116	1500	0.01	0.01	0.157589	-1.291290	0.152023	0.656395	0.0178571	WORN	WORN
117	1500	0.01	0.02	0.063453	-1.435760	0.032967	0.292016	0.0178571	WORN	WORN
118	1500	0.01	0.03	0.055208	-1.446460	0.025334	0.215102	0.0178571	WORN	WORN
119	1500	0.02	0.01	0.117071	-1.336020	0.112738	0.365672	0.0178571	WORN	WORN
120	1500	0.02	0.02	0.056203	-1.453060	0.020237	0.232624	0.0178571	WORN	WORN
121	1500	0.02	0.03	0.107004	-1.370960	0.072285	0.376459	0.0178571	WORN	WORN
122	1500	0.03	0.01	0.055585	-1.457880	0.015246	0.276197	0.0178571	WORN	WORN
123	1500	0.03	0.02	0.050537	-1.452760	0.014884	0.178972	0.0178571	WORN	WORN
124	1500	0.03	0.03	0.047862	-1.437610	0.016674	0.297443	0.0178571	WORN	WORN
125	500	0.01	0.01	0.100055	-1.470160	0.093468	0.686569	0.0196429	WORN	WORN
126	500	0.01	0.02	0.209996	-1.218690	0.234267	0.740184	0.0196429	WORN	WORN
127	500	0.01	0.03	0.263045	-1.225780	0.262741	0.488878	0.0196429	WORN	WORN
128	500	0.02	0.01	0.136591	-1.382830	0.095073	0.174890	0.0196429	WORN	WORN
129	500	0.02	0.02	0.202106	-1.316950	0.205890	0.764623	0.0196429	WORN	WORN
130	500	0.02	0.03	0.263222	-1.203370	0.274163	0.639435	0.0196429	WORN	WORN
131	500	0.03	0.01	0.093653	-1.433570	0.069762	0.237702	0.0196429	WORN	WORN
132	500	0.03	0.02	0.130613	-1.365180	0.086148	0.216416	0.0196429	WORN	WORN
133	500	0.03	0.03	0.169972	-1.281700	0.473717	0.344965	0.0196429	WORN	WORN
134	1000	0.01	0.01	0.141437	-1.340220	0.107337	0.496698	0.0196429	WORN	WORN
135	1000	0.01	0.02	0.136160	-1.405200	0.109900	0.537761	0.0196429	WORN	WORN
136	1000	0.01	0.03	0.136509	-1.428260	0.085895	0.655720	0.0196429	WORN	WORN
137	1000	0.02	0.01	0.164782	-1.384120	0.130099	0.527382	0.0196429	WORN	WORN
138	1000	0.02	0.02	0.069074	-1.472770	0.040384	0.581718	0.0196429	WORN	WORN

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
139	1000	0.02	0.03	0.083036	-1.434090	0.057638	0.213107	0.0196429	WORN	WORN
140	1000	0.03	0.01	0.089061	-1.390360	0.071099	0.360255	0.0196429	WORN	WORN
141	1000	0.03	0.02	0.129930	-1.301870	0.119924	0.703936	0.0196429	WORN	WORN
142	1000	0.03	0.03	0.093309	-1.397360	0.072610	0.288930	0.0196429	WORN	WORN
143	1500	0.01	0.01	0.145512	-1.284870	0.153674	0.824825	0.0196429	WORN	WORN
144	1500	0.01	0.02	0.053089	-1.444680	0.026089	0.289323	0.0196429	WORN	WORN
145	1500	0.01	0.03	0.050351	-1.422360	0.035597	0.614931	0.0196429	WORN	WORN
146	1500	0.02	0.01	0.074912	-1.403550	0.056803	0.418429	0.0196429	WORN	WORN
147	1500	0.02	0.02	0.048519	-1.455410	0.015859	0.361737	0.0196429	WORN	WORN
148	1500	0.02	0.03	0.098481	-1.351090	0.073955	0.316378	0.0196429	WORN	WORN
149	1500	0.03	0.01	0.045046	-1.440340	0.014226	0.309521	0.0196429	WORN	WORN
150	1500	0.03	0.02	0.041082	-1.458570	0.005388	0.415361	0.0196429	WORN	WORN
151	1500	0.03	0.03	0.039146	-1.459650	0.001581	0.272750	0.0196429	WORN	WORN

APPENDIX H. PREPROCESSED DATA

Train Data

Exp #	S	F	D	X	Y	Z	W	Tool Wear
1	-1	-1	-1	-0.308456	-0.071341	-0.282220	-0.262844	0.134634
2	-1	-1	-1	-0.429075	-0.120856	-0.147419	-0.201173	0.134634
3	-1	-1	-1	-0.510940	-0.435975	-0.156421	-0.106198	0.134634
4	-1	-1	0	0.379319	0.387320	0.945019	0.007935	0.134634
5	-1	-1	0	0.523924	0.846280	0.472362	0.513566	0.134634
6	-1	-1	0	0.312632	0.735652	0.947303	0.452805	0.134634
7	-1	-1	1	0.101341	0.285292	0.911929	0.131816	0.134634
8	-1	-1	1	0.292314	0.675857	0.876554	0.035179	0.134634
9	-1	-1	1	0.614944	0.731400	0.683592	0.000553	0.134634
10	-1	0	-1	-0.260037	-0.565193	-0.378387	-0.397969	0.134634
11	-1	0	-1	-0.413079	-0.549385	-0.314800	-0.642430	0.134634
12	-1	0	-1	-0.294867	-0.386465	-0.293529	-0.718243	0.134634
13	-1	0	0	0.161627	0.016344	0.018411	0.285234	0.134634
14	-1	0	0	0.240568	0.455217	0.633860	0.073346	0.134634
15	-1	0	0	0.233885	0.762092	0.326754	0.072116	0.134634
16	-1	0	1	0.712885	0.828063	0.432555	-0.214260	0.134634
17	-1	0	1	0.522260	0.894034	0.816147	0.059918	0.134634
18	-1	0	1	0.923642	0.999990	0.593119	-0.141219	0.134634
19	-1	1	-1	-0.045437	-0.122595	-0.208086	-0.564468	0.134634
20	-1	1	-1	-0.214585	-0.127271	-0.135614	-0.501972	0.134634
21	-1	1	-1	-0.247712	-0.041797	0.006050	-0.401964	0.134634
22	-1	1	0	-0.089002	-0.119386	-0.144246	-0.802364	0.134634
23	-1	1	0	0.216728	-0.371211	-0.127335	-0.839807	0.134634
24	-1	1	0	-0.158908	-0.258933	-0.156115	-0.869964	0.134634
25	-1	1	1	0.049789	0.225622	0.680305	-0.257150	0.134634
26	-1	1	1	-0.086129	-0.061066	0.089493	-0.427493	0.134634
27	-1	1	1	0.093786	-0.060762	0.256421	-0.459527	0.134634
28	0	-1	-1	-0.397029	-0.613101	-0.395850	-0.829232	0.134634
29	0	-1	-1	-0.366056	-0.618350	-0.353277	-0.754033	0.134634
30	0	-1	-1	-0.330625	-0.560632	-0.417955	-0.651387	0.134634
31	0	-1	0	-0.330844	0.264980	0.365855	-0.065742	0.134634
32	0	-1	0	-0.044290	0.112024	0.372504	0.098652	0.134634
33	0	-1	0	0.203261	0.616567	0.166322	0.265204	0.134634
34	0	-1	1	-0.236391	-0.341121	-0.145212	-0.607143	0.134634
35	0	-1	1	-0.300319	-0.026117	-0.323948	-0.680996	0.134634
36	0	-1	1	-0.116981	-0.353919	-0.299875	-0.524194	0.134634
37	0	0	-1	-0.077849	0.120273	-0.085814	0.179997	0.134634
38	0	0	-1	-0.109566	-0.216663	-0.027004	-0.527890	0.134634
39	0	0	-1	0.078230	-0.140230	-0.313944	-0.120490	0.134634
40	0	0	0	-0.270383	-0.323175	-0.259491	-0.418339	0.134634
41	0	0	0	-0.318945	-0.402165	-0.374950	-0.236876	0.134634
42	0	0	0	-0.338670	-0.301183	-0.091739	-0.360203	0.134634
43	0	0	1	-0.274798	-0.440942	-0.269948	-0.830251	0.134634

Exp #	S	F	D	X	Y	Z	W	Tool Wear
44	0	0	1	-0.260916	-0.395743	-0.423239	-0.835387	0.134634
45	0	0	1	-0.403477	-0.354585	-0.226882	-0.831228	0.134634
46	0	1	-1	0.067752	-0.191124	-0.478961	-0.168567	0.134634
47	0	1	-1	-0.313867	-0.228468	-0.001658	-0.382709	0.134634
48	0	1	-1	-0.198535	-0.380217	-0.243533	-0.295003	0.134634
49	0	1	0	-0.235567	-0.155553	-0.167655	-0.643828	0.134634
50	0	1	0	-0.160659	-0.333178	-0.293130	-0.434647	0.134634
51	0	1	0	-0.420278	-0.094085	0.345964	-0.424613	0.134634
52	0	1	1	-0.196215	-0.454583	-0.273442	-0.601073	0.134634
53	0	1	1	-0.297893	-0.391219	-0.222679	-0.423818	0.134634
54	0	1	1	-0.188738	-0.542838	-0.390905	-0.466320	0.134634
55	1	-1	-1	-0.174006	-0.011485	0.019292	0.466719	0.134634
56	1	-1	-1	-0.000846	-0.259922	-0.204446	0.002190	0.134634
57	1	-1	-1	-0.017263	0.162193	-0.133296	-0.050867	0.134634
58	1	-1	0	-0.429775	-0.482554	-0.298684	-0.641985	0.134634
59	1	-1	0	-0.281480	-0.483614	-0.334412	-0.565613	0.134634
60	1	-1	0	-0.310540	-0.499265	-0.413095	-0.763971	0.134634
61	1	-1	1	-0.253922	-0.588856	-0.440170	-0.951351	0.134634
62	1	-1	1	-0.309438	-0.512026	-0.406935	-0.949443	0.134634
63	1	-1	1	-0.285074	-0.469879	-0.358735	-0.984597	0.134634
64	1	0	-1	-0.543771	-0.422259	-0.286946	-0.787986	0.134634
65	1	0	-1	-0.396900	-0.529427	-0.431253	-0.597524	0.134634
66	1	0	-1	-0.411372	-0.536323	-0.354377	-0.764853	0.134634
67	1	0	0	-0.354058	-0.551036	-0.397326	-0.373536	0.134634
68	1	0	0	-0.202568	-0.512455	-0.410888	-0.747486	0.134634
69	1	0	0	-0.271999	-0.520491	-0.434594	-0.605027	0.134634
70	1	0	1	-0.389602	-0.101727	-0.185735	-0.496883	0.134634
71	1	0	1	-0.434010	-0.282289	-0.274287	-0.483196	0.134634
72	1	0	1	-0.340425	-0.369381	-0.177417	-0.256851	0.134634
73	1	1	-1	-0.357593	-0.460608	-0.383247	-0.783902	0.134634
74	1	1	-1	-0.275827	-0.544178	-0.363067	-0.729899	0.134634
75	1	1	-1	-0.450764	-0.472639	-0.309092	-0.857486	0.134634
76	1	1	0	-0.362649	-0.482879	-0.433254	-0.786632	0.134634
77	1	1	0	-0.335834	-0.466447	-0.317916	-0.662662	0.134634
78	1	1	0	-0.340333	-0.474211	-0.365513	-0.538418	0.134634
79	1	1	1	-0.363480	-0.538307	-0.402478	-1.000000	0.134634
80	1	1	1	-0.334428	-0.529617	-0.424626	-0.966430	0.134634
81	1	1	1	-0.333742	-0.540996	-0.391636	-0.912978	0.134634
82	-1	-1	-1	-0.218183	-0.576205	-0.199226	-0.287997	0.519238
83	-1	-1	-1	-0.467254	-0.309148	-0.304934	-0.252396	0.519238
84	-1	-1	-1	-0.079223	-0.295890	-0.097084	-0.339060	0.519238
85	-1	-1	0	0.097783	0.217581	0.281050	-0.380590	0.519238
86	-1	-1	0	0.342938	0.866138	0.138017	-0.248882	0.519238
87	-1	-1	0	-0.228111	0.132184	0.190759	-0.179800	0.519238
88	-1	-1	1	0.054442	0.359675	0.275253	0.119043	0.519238
89	-1	-1	1	0.122685	-0.129014	-0.308977	-0.201906	0.519238
90	-1	-1	1	-0.413695	0.010694	0.242884	0.345151	0.519238

Exp #	S	F	D	X	Y	Z	W	Tool Wear
91	-1	0	-1	-0.127646	-0.238755	0.013206	-0.841978	0.519238
92	-1	0	-1	0.026690	-0.203556	-0.160325	-0.840905	0.519238
93	-1	0	-1	-0.120399	-0.150032	0.480401	-0.710599	0.519238
94	-1	0	0	-0.475325	0.216665	0.387261	0.430681	0.519238
95	-1	0	0	-0.056490	-0.180379	-0.046624	0.262614	0.519238
96	-1	0	0	-0.161890	0.114532	0.011669	0.142672	0.519238
97	-1	0	1	-0.060967	-0.134246	-0.177036	0.010286	0.519238
98	-1	0	1	0.212735	-0.030739	0.301013	-0.122475	0.519238
99	-1	0	1	-0.161169	-0.160020	0.324551	-0.064845	0.519238
100	-1	1	-1	-0.060967	-0.134246	-0.177036	0.010286	0.519238
101	-1	1	-1	0.212735	-0.030739	0.301013	-0.122475	0.519238
102	-1	1	-1	-0.161169	-0.160020	0.324551	-0.064845	0.519238
103	-1	1	0	-0.111848	-0.352692	-0.086691	-0.630705	0.519238
104	-1	1	0	-0.006961	-0.222627	-0.260240	-0.696861	0.519238
105	-1	1	0	-0.095494	-0.497418	-0.164083	-0.822073	0.519238
106	-1	1	1	-0.218340	-0.047529	0.004917	-0.696582	0.519238
107	-1	1	1	-0.223059	0.169785	0.116707	-0.424010	0.519238
108	-1	1	1	-0.084898	-0.197198	-0.111466	-0.475732	0.519238
109	0	-1	-1	-0.277399	-0.076587	-0.105851	0.008475	0.519238
110	0	-1	-1	-0.407774	-0.182296	-0.150235	-0.142415	0.519238
111	0	-1	-1	-0.178864	-0.149993	-0.064953	-0.329235	0.519238
112	0	-1	0	-0.165910	-0.295618	-0.184719	-0.444843	0.519238
113	0	-1	0	-0.153515	-0.252128	-0.072615	-0.215616	0.519238
114	0	-1	0	-0.377113	-0.154521	0.258938	-0.240576	0.519238
115	0	-1	1	-0.227327	-0.337195	-0.326779	-0.544841	0.519238
116	0	-1	1	-0.151848	-0.514816	-0.383550	-0.598616	0.519238
117	0	-1	1	-0.401850	-0.209334	-0.287988	-0.666535	0.519238
118	0	0	-1	-0.385679	-0.282581	-0.273770	-0.818741	0.519238
119	0	0	-1	-0.240308	-0.443874	-0.244862	-0.509106	0.519238
120	0	0	-1	-0.081238	-0.408937	-0.303555	-0.713154	0.519238
121	0	0	0	-0.294501	-0.492980	-0.265948	-0.464809	0.519238
122	0	0	0	-0.388236	-0.387033	-0.208300	-0.445627	0.519238
123	0	0	0	-0.316032	-0.433110	-0.299800	-0.522949	0.519238
124	0	0	1	-0.320517	-0.434067	-0.296460	-0.904546	0.519238
125	0	0	1	-0.264598	-0.571537	-0.352157	-0.821108	0.519238
126	0	0	1	-0.233332	-0.479705	-0.367131	-0.914533	0.519238
127	0	1	-1	-0.267045	-0.080281	-0.635364	-0.532950	0.519238
128	0	1	-1	-0.182217	-0.362773	-0.515994	-0.244821	0.519238
129	0	1	-1	-0.114409	-0.438589	-0.309159	-0.537518	0.519238
130	0	1	0	-0.472299	-0.101675	0.002328	-0.622619	0.519238
131	0	1	0	-0.356336	0.005494	-0.043361	-0.462857	0.519238
132	0	1	0	-0.084078	-0.413861	-0.063224	-0.465350	0.519238
133	0	1	1	-0.296615	-0.539554	-0.305537	-0.556700	0.519238
134	0	1	1	-0.184070	-0.384143	-0.419285	-0.368188	0.519238
135	0	1	1	-0.273523	-0.246843	-0.325314	-0.422468	0.519238
136	1	-1	-1	-0.220033	-0.333362	-0.331264	-0.121751	0.519238
137	1	-1	-1	-0.339714	-0.168718	-0.037942	0.248248	0.519238

Exp #	S	F	D	X	Y	Z	W	Tool Wear
138	1	-1	-1	-0.319656	-0.258188	-0.092759	0.223968	0.519238
139	1	-1	0	-0.370478	-0.511727	-0.342163	-0.759153	0.519238
140	1	-1	0	-0.384715	-0.573785	-0.359715	-0.640522	0.519238
141	1	-1	0	-0.254134	-0.550299	-0.238495	-0.720992	0.519238
142	1	-1	1	-0.465693	-0.658693	-0.477499	-0.921850	0.519238
143	1	-1	1	-0.480934	-0.586365	-0.571652	-0.925950	0.519238
144	1	-1	1	-0.483085	-0.595944	-0.469959	-0.970304	0.519238
145	1	0	-1	-0.605668	-0.443421	-0.436238	-0.736093	0.519238
146	1	0	-1	-0.469335	-0.558793	-0.459783	-0.580072	0.519238
147	1	0	-1	-0.384521	-0.481591	-0.378587	-0.740584	0.519238
148	1	0	0	0.236615	0.401423	0.821174	-0.707710	0.519238
149	1	0	0	0.857751	0.432056	0.856560	-0.776739	0.519238
150	1	0	0	0.877740	0.261274	0.753055	-0.857458	0.519238
151	1	0	1	0.912446	0.426835	1.000014	-0.591872	0.519238
152	1	0	1	1.000007	0.481123	0.739554	-0.366365	0.519238
153	1	0	1	0.945812	0.299907	0.785400	-0.720882	0.519238
154	1	1	-1	0.891618	0.340852	0.887571	-0.823879	0.519238
155	1	1	-1	0.878091	0.282965	0.858789	-0.833887	0.519238
156	1	1	-1	0.864565	0.342559	0.840203	-0.807103	0.519238
157	1	1	0	0.940769	0.428294	0.799073	-0.789931	0.519238
158	1	1	0	0.886030	0.331292	0.828665	-0.916764	0.519238
159	1	1	0	0.875578	0.338422	0.842402	-0.895287	0.519238
160	1	1	1	-0.471086	-0.689973	-0.550214	-0.836949	0.519238
161	1	1	1	-0.443187	-0.636612	-0.495540	-0.675760	0.519238
162	1	1	1	-0.518659	-0.658612	-0.498627	-0.622196	0.519238
163	-1	-1	-1	-0.677494	-0.591271	-0.548239	-0.343110	0.903841
164	-1	-1	-1	-0.758519	-0.725556	-0.503441	-0.403820	0.903841
165	-1	-1	-1	-0.829996	-0.787780	-0.654517	-0.383340	0.903841
166	-1	-1	0	0.209786	0.612418	-0.200292	0.139433	0.903841
167	-1	-1	0	-0.216813	0.080442	0.096895	-0.270439	0.903841
168	-1	-1	0	0.039615	0.246958	0.500856	-0.104738	0.903841
169	-1	-1	1	-0.188361	-0.012597	-0.079082	0.320306	0.903841
170	-1	-1	1	-0.327591	0.030717	-0.180205	-0.005159	0.903841
171	-1	-1	1	-0.176476	0.061159	0.167106	-0.035434	0.903841
172	-1	0	-1	-0.238227	-0.153375	-0.152546	-0.730889	0.903841
173	-1	0	-1	0.190584	0.104093	0.059990	-0.859456	0.903841
174	-1	0	-1	-0.319938	-0.106554	-0.182619	-0.698999	0.903841
175	-1	0	0	-0.295131	-0.403226	-0.305530	0.510908	0.903841
176	-1	0	0	-0.206851	-0.467669	-0.070354	0.409401	0.903841
177	-1	0	0	-0.442924	-0.252942	-0.043803	0.581111	0.903841
178	-1	0	1	-0.052387	0.220973	0.073816	-0.028369	0.903841
179	-1	0	1	-0.223125	0.695084	0.472754	-0.128112	0.903841
180	-1	0	1	-0.242850	0.207091	0.142955	-0.037474	0.903841
181	-1	1	-1	-0.351489	-0.467696	-0.346467	-0.795633	0.903841
182	-1	1	-1	-0.336651	-0.382578	-0.612108	-0.718868	0.903841
183	-1	1	-1	-0.429309	-0.488158	-0.285033	-0.486605	0.903841
184	-1	1	0	-0.497091	-0.167809	-0.429485	-0.824203	0.903841

Exp #	S	F	D	X	Y	Z	W	Tool Wear
185	-1	1	0	-0.294548	-0.154568	-0.326715	-0.860912	0.903841
186	-1	1	0	-0.069841	-0.151913	-0.087514	-0.895361	0.903841
187	-1	1	1	-0.797943	-0.667522	-0.798486	-0.449061	0.903841
188	-1	1	1	-0.797207	-0.696451	-0.774040	-0.489246	0.903841
189	-1	1	1	-0.859996	-0.696030	-0.870751	-0.488336	0.903841
190	0	-1	-1	-0.576047	-0.331606	-0.318825	-0.268467	0.903841
191	0	-1	-1	-0.420425	-0.294531	-0.316440	-0.149097	0.903841
192	0	-1	-1	-0.573317	-0.435821	-0.425977	-0.091121	0.903841
193	0	-1	0	-0.468895	-0.434562	-0.108075	-0.390724	0.903841
194	0	-1	0	-0.341238	-0.468142	-0.524084	-0.302896	0.903841
195	0	-1	0	-0.414651	-0.044396	-0.162411	-0.282319	0.903841
196	0	-1	1	-0.350969	-0.680381	-0.344000	-0.360104	0.903841
197	0	-1	1	-0.482554	-0.637854	-0.376034	-0.567609	0.903841
198	0	-1	1	-0.485920	-0.552307	-0.373627	-0.328173	0.903841
199	0	0	-1	-0.560780	-0.155655	-0.411249	-0.342193	0.903841
200	0	0	-1	-0.355017	-0.497267	-0.372825	-0.561083	0.903841
201	0	0	-1	-0.639315	-0.202731	-0.274030	-0.263064	0.903841
202	0	0	0	-0.432277	-0.653223	-0.639511	-0.461315	0.903841
203	0	0	0	-0.427309	-0.741525	-0.465990	-0.057600	0.903841
204	0	0	0	-0.616651	-0.512981	-0.528533	-0.430562	0.903841
205	0	0	1	-0.621993	-0.522426	-0.397811	-0.966573	0.903841
206	0	0	1	-0.366100	-0.639659	-0.524194	-0.793848	0.903841
207	0	0	1	-0.436267	-0.665004	-0.605123	-0.817363	0.903841
208	0	1	-1	-0.581821	-0.417895	-0.439757	-0.672871	0.903841
209	0	1	-1	-0.513398	-0.263510	-0.338445	-0.631521	0.903841
210	0	1	-1	-0.322737	-0.249537	-0.343639	-0.466384	0.903841
211	0	1	0	-0.519454	-0.437031	-0.421663	-0.651066	0.903841
212	0	1	0	-0.298663	-0.483573	-0.520925	-0.656793	0.903841
213	0	1	0	-0.598483	-0.425767	-0.553234	-0.715347	0.903841
214	0	1	1	-0.340476	-0.348731	-0.344930	-0.722328	0.903841
215	0	1	1	-0.484726	-0.322764	-0.408671	-0.561404	0.903841
216	0	1	1	-0.538663	-0.636637	-0.456931	-0.733967	0.903841
217	1	-1	-1	-0.353193	-0.638523	-0.201276	0.543170	0.903841
218	1	-1	-1	-0.328163	-0.179965	-0.450617	0.288456	0.903841
219	1	-1	-1	-0.218219	-0.556437	-0.573339	0.219856	0.903841
220	1	-1	0	-0.499238	-0.556655	-0.512735	-0.744109	0.903841
221	1	-1	0	-0.425320	-0.638170	-0.553826	-0.583045	0.903841
222	1	-1	0	-0.466078	-0.717260	-0.421895	-0.805366	0.903841
223	1	-1	1	-0.445082	-0.527922	-0.474533	-0.892237	0.903841
224	1	-1	1	-0.417974	-0.606895	-0.415894	-0.731939	0.903841
225	1	-1	1	-0.482506	-0.625007	-0.467962	-0.879767	0.903841
226	1	0	-1	-0.356435	-0.545924	-0.470586	-0.724497	0.903841
227	1	0	-1	-0.345737	-0.551516	-0.370750	-0.650774	0.903841
228	1	0	-1	-0.384979	-0.464485	-0.358432	-0.457467	0.903841
229	1	0	0	-0.522861	-0.618725	-0.564372	-0.823607	0.903841
230	1	0	0	-0.422693	-0.609851	-0.497205	-0.192865	0.903841
231	1	0	0	-0.516465	-0.617789	-0.486298	-0.672127	0.903841

Exp #	S	F	D	X	Y	Z	W	Tool Wear
232	1	0	1	-0.323601	-0.454663	-0.429585	-0.714341	0.903841
233	1	0	1	-0.371405	-0.468154	-0.449137	-0.768032	0.903841
234	1	0	1	-0.427005	-0.483021	-0.356899	-0.486286	0.903841
235	1	1	-1	-0.468632	-0.669041	-0.544673	-0.613172	0.903841
236	1	1	-1	-0.459670	-0.685326	-0.564475	-0.632081	0.903841
237	1	1	-1	-0.523909	-0.613990	-0.495436	-0.515853	0.903841
238	1	1	0	-0.511339	-0.677425	-0.568639	-0.784122	0.903841
239	1	1	0	-0.491171	-0.597281	-0.504966	-0.824491	0.903841
240	1	1	0	-0.504360	-0.683127	-0.557594	-0.864070	0.903841
241	1	1	1	-0.563524	-0.653975	-0.536313	-0.785741	0.903841
242	1	1	1	-0.596029	-0.631939	-0.538823	-0.733386	0.903841
243	1	1	1	-0.561989	-0.744031	-0.588316	-0.854347	0.903841
244	-1	-1	-1	-0.794435	-0.717233	-0.681389	-0.123330	1.000000
245	-1	-1	-1	-0.566913	-0.398234	-0.196834	-0.209712	1.000000
246	-1	-1	-1	-0.705264	-0.745628	-0.710165	-0.159040	1.000000
247	-1	-1	0	0.110984	0.015274	0.429756	-0.277148	1.000000
248	-1	-1	0	0.405441	0.452716	0.222636	-0.135040	1.000000
249	-1	-1	0	0.141857	-0.122181	0.184042	0.196452	1.000000
250	-1	-1	1	-0.190082	-0.225145	-0.007680	0.235483	1.000000
251	-1	-1	1	-0.336146	-0.086637	-0.008920	0.338870	1.000000
252	-1	-1	1	-0.278949	0.058073	-0.091383	0.071565	1.000000
253	-1	0	-1	-0.145972	0.128157	0.012953	-0.848434	1.000000
254	-1	0	-1	-0.217234	-0.277006	-0.164907	-0.840471	1.000000
255	-1	0	-1	-0.308914	-0.122350	-0.312814	-0.886368	1.000000
256	-1	0	0	-0.388492	-0.312183	-0.368083	0.266779	1.000000
257	-1	0	0	-0.481414	0.060221	-0.283464	0.412640	1.000000
258	-1	0	0	-0.302253	-0.224679	-0.065933	0.314905	1.000000
259	-1	0	1	0.093046	0.359937	-0.042545	-0.090525	1.000000
260	-1	0	1	-0.156974	0.503091	0.359013	-0.114920	1.000000
261	-1	0	1	-0.142521	0.435512	0.135339	0.108548	1.000000
262	-1	1	-1	-0.510581	-0.606184	-0.536138	-0.756764	1.000000
263	-1	1	-1	-0.337820	-0.634699	-0.543679	-0.867165	1.000000
264	-1	1	-1	-0.471017	-0.453483	-0.374793	-0.797867	1.000000
265	-1	1	0	-0.492958	-0.522122	-0.493468	-0.722978	1.000000
266	-1	1	0	-0.469097	-0.451237	-0.467934	-0.860555	1.000000
267	-1	1	0	-0.498985	-0.416486	-0.232772	-0.741710	1.000000
268	-1	1	1	-0.427173	-0.102503	-0.126872	-0.469028	1.000000
269	-1	1	1	-0.500817	-0.299537	-0.377335	-0.614306	1.000000
270	-1	1	1	-0.348339	0.410326	-0.041490	-0.506494	1.000000
271	0	-1	-1	-0.435303	-0.296520	-0.428883	-0.238932	1.000000
272	0	-1	-1	-0.625327	-0.407446	-0.275271	-0.041341	1.000000
273	0	-1	-1	-0.333636	0.095334	-0.293754	-0.040080	1.000000
274	0	-1	0	-0.170764	-0.291408	-0.441236	-0.154680	1.000000
275	0	-1	0	-0.391160	-0.470959	-0.337133	-0.170277	1.000000
276	0	-1	0	-0.155816	-0.509557	-0.533617	-0.164790	1.000000
277	0	-1	1	-0.551566	-0.535049	-0.535518	-0.360019	1.000000
278	0	-1	1	-0.424433	-0.584557	-0.487557	-0.377254	1.000000

Exp #	S	F	D	X	Y	Z	W	Tool Wear
279	0	-1	1	-0.486488	-0.581878	-0.623652	-0.389521	1.000000
280	0	0	-1	-0.563521	-0.480320	-0.504631	-0.722978	1.000000
281	0	0	-1	-0.339190	-0.473237	-0.653177	-0.434372	1.000000
282	0	0	-1	-0.438205	-0.474042	-0.457077	0.159328	1.000000
283	0	0	0	-0.473578	-0.519325	-0.247893	-0.061703	1.000000
284	0	0	0	-0.530555	-0.344411	-0.292962	0.228984	1.000000
285	0	0	0	-0.451727	-0.347477	-0.334131	0.184377	1.000000
286	0	0	1	-0.313391	-0.524077	-0.479425	-0.867119	1.000000
287	0	0	1	-0.340590	-0.343245	-0.550727	-0.865654	1.000000
288	0	0	1	-0.340718	-0.559584	-0.394196	-0.770937	1.000000
289	0	1	-1	-0.725044	-0.751303	-0.612097	-0.468828	1.000000
290	0	1	-1	-0.724629	-0.596191	-0.675178	-0.686607	1.000000
291	0	1	-1	-0.826689	-0.772147	-0.798191	-0.407899	1.000000
292	0	1	0	-0.790639	-0.443291	-0.575695	-0.503366	1.000000
293	0	1	0	-0.650101	-0.509856	-0.544349	-0.527812	1.000000
294	0	1	0	-0.579560	-0.357615	-0.616686	-0.171587	1.000000
295	0	1	1	-0.642832	-0.508913	-0.615356	-0.760203	1.000000
296	0	1	1	-0.772308	-0.767025	-0.815237	-0.637895	1.000000
297	0	1	1	-0.709663	-0.716200	-0.675963	-0.656304	1.000000
298	1	-1	-1	-0.634105	-0.560054	-0.628886	0.561608	1.000000
299	1	-1	-1	-0.724323	-0.473866	-0.436569	0.455017	1.000000
300	1	-1	-1	-0.613167	-0.408198	-0.587596	0.631822	1.000000
301	1	-1	0	-0.894728	-0.783100	-0.882739	-0.818083	1.000000
302	1	-1	0	-0.892197	-0.829251	-0.871534	-0.676137	1.000000
303	1	-1	0	-0.870768	-0.790538	-0.847919	-0.728020	1.000000
304	1	-1	1	-0.887300	-0.789889	-0.813687	-0.690875	1.000000
305	1	-1	1	-0.736563	-0.567334	-0.696114	-0.587359	1.000000
306	1	-1	1	-0.892159	-0.758315	-0.794947	-0.531820	1.000000
307	1	0	-1	-0.715842	-0.591751	-0.678690	-0.508260	1.000000
308	1	0	-1	-0.798834	-0.693448	-0.644741	-0.292986	1.000000
309	1	0	-1	-0.753110	-0.689069	-0.663092	-0.492929	1.000000
310	1	0	0	-0.919525	-0.863987	-0.920190	-0.666081	1.000000
311	1	0	0	-0.885152	-0.881476	-0.932106	-0.617027	1.000000
312	1	0	0	-0.856143	-0.870189	-0.896280	-0.601146	1.000000
313	1	0	1	-0.815749	-0.731677	-0.835978	-0.485225	1.000000
314	1	0	1	-0.769942	-0.718617	-0.660728	-0.738770	1.000000
315	1	0	1	-0.752500	-0.554553	-0.657295	-0.253424	1.000000
316	1	1	-1	-0.963868	-0.888448	-0.940291	-0.565952	1.000000
317	1	1	-1	-0.940059	-0.889793	-0.933518	-0.599486	1.000000
318	1	1	-1	-0.984310	-0.949472	-0.944185	-0.398815	1.000000
319	1	1	0	-1.000017	-0.999989	-0.999983	-0.772224	1.000000
320	1	1	0	-0.988595	-0.992387	-0.963368	-0.772468	1.000000
321	1	1	0	-0.983024	-0.965159	-0.966495	-0.293571	1.000000
322	1	1	1	-0.977949	-0.957434	-0.934008	-0.744016	1.000000
323	1	1	1	-0.946489	-0.907900	-0.861817	-0.858071	1.000000
324	1	1	1	-0.952632	-0.944937	-0.904923	-0.613471	1.000000

Test Data

Exp #	S	F	D	X	Y	Z	W	Tool Wear
1	-1	-1	-1	-0.635125	-0.738802	-0.950927	-0.654110	0.000000
2	-1	-1	0	0.116304	-0.288510	0.056921	0.199853	0.000000
3	-1	-1	1	-0.786263	-0.677529	-0.731276	-0.699125	0.000000
4	-1	0	-1	-0.254099	-0.537727	-0.322592	-0.889661	0.000000
5	-1	0	0	-0.086368	-0.297636	-0.139839	0.134731	0.000000
6	-1	0	1	0.183502	-0.367227	0.183329	-0.527837	0.000000
7	-1	1	-1	-0.500650	-0.674550	-0.452994	-0.548992	0.000000
8	-1	1	0	-0.463875	-0.501845	-0.467408	-0.647929	0.000000
9	-1	1	1	-0.024457	-0.270259	0.057431	-0.687330	0.000000
10	0	-1	-1	-0.271922	-0.400377	-0.300604	-0.203331	0.000000
11	0	-1	0	-0.938414	-0.793649	-0.958632	-0.723779	0.000000
12	0	-1	1	-0.608292	-0.609615	-0.639226	-0.555304	0.000000
13	0	0	-1	-0.577336	-0.710804	-0.662119	-0.625145	0.000000
14	0	0	0	-0.816370	-0.767451	-0.907476	-0.524073	0.000000
15	0	0	1	-0.835744	-0.737933	-0.794896	-0.762650	0.000000
16	0	1	-1	-0.659364	-0.565663	-0.675788	-0.581953	0.000000
17	0	1	0	-0.525718	-0.413165	-0.641667	-0.630727	0.000000
18	0	1	1	-0.539334	-0.486977	-0.504886	-0.404168	0.000000
19	1	-1	-1	-0.381045	-0.312783	-0.519977	0.179457	0.000000
20	1	-1	0	-0.868265	-0.750628	-0.912345	-0.492013	0.000000
21	1	-1	1	-0.887774	-0.767110	-0.940194	-0.741480	0.000000
22	1	0	-1	-0.755461	-0.642486	-0.854881	-0.838014	0.000000
23	1	0	0	-0.870806	-0.780767	-0.967395	-0.811414	0.000000
24	1	0	1	-0.665246	-0.528788	-0.814366	-0.643419	0.000000
25	1	1	-1	-0.909594	-0.773131	-0.931446	-0.771035	0.000000
26	1	1	0	-0.945756	-0.770990	-0.963626	-0.271088	0.000000
27	1	1	1	-0.964082	-0.788620	-1.000000	-0.489594	0.000000
28	-1	-1	-1	-0.327128	-0.519724	-0.450028	-0.361005	0.134634
29	-1	-1	0	0.552400	0.552446	0.008724	0.595233	0.134634
30	-1	-1	1	-0.111172	0.331879	0.663004	-0.108371	0.134634
31	-1	0	-1	-0.774744	-0.650587	-0.725667	-0.655043	0.134634
32	-1	0	0	0.576696	0.307823	0.204464	0.516695	0.134634
33	-1	0	1	0.071636	0.756178	0.566780	0.212884	0.134634
34	-1	1	-1	-0.433424	-0.372565	-0.477098	-0.108190	0.134634
35	-1	1	0	-0.291022	-0.360460	-0.555998	-0.592881	0.134634
36	-1	1	1	0.386435	0.169604	-0.150857	-0.057703	0.134634
37	0	-1	-1	-0.909490	-0.750907	-0.779791	-0.614297	0.134634
38	0	-1	0	-0.035154	0.091942	-0.009003	0.171390	0.134634
39	0	-1	1	-0.400191	-0.337770	-0.228385	-0.231607	0.134634
40	0	0	-1	-0.285180	-0.204734	-0.304602	0.240980	0.134634
41	0	0	0	-0.684260	-0.596920	-0.577634	-0.200720	0.134634
42	0	0	1	-0.840845	-0.657261	-0.715392	-0.723574	0.134634
43	0	1	-1	-0.502234	-0.438990	-0.445432	-0.587035	0.134634
44	0	1	0	-0.206121	-0.252349	-0.278241	0.037949	0.134634
45	0	1	1	-0.576450	-0.451778	-0.506483	-0.597497	0.134634
46	1	-1	-1	0.014386	0.046687	0.044699	0.273882	0.134634

Exp #	S	F	D	X	Y	Z	W	Tool Wear
47	1	-1	0	-0.793588	-0.705403	-0.699227	-0.562378	0.134634
48	1	-1	1	-0.850101	-0.779619	-0.776520	-1.000000	0.134634
49	1	0	-1	-0.740344	-0.640844	-0.796942	-0.785602	0.134634
50	1	0	0	-0.838520	-0.724523	-0.772541	-0.808123	0.134634
51	1	0	1	-0.626506	-0.529346	-0.604424	-0.442888	0.134634
52	1	1	-1	-0.845159	-0.733928	-0.747251	-0.797043	0.134634
53	1	1	0	-0.898224	-0.745165	-0.805948	-0.091812	0.134634
54	1	1	1	-0.923571	-0.789831	-0.822812	-0.714133	0.134634
55	-0.75	-0.5	-0.5	-0.503677	-0.479838	-0.362690	-0.414163	0.326923
56	-0.75	-0.5	0.5	-0.636630	-0.607659	-0.591382	-0.522932	0.326923
57	-0.75	0.5	-0.5	0.245186	-0.438431	-0.426548	-0.065504	0.326923
58	-0.75	0.5	0.5	-0.374470	-0.269203	-0.261714	-0.268688	0.326923
59	-0.25	-0.5	-0.5	0.109400	-0.320046	-0.164857	-0.494718	0.326923
60	-0.25	-0.5	0.5	-0.650013	-0.605269	-0.819154	-0.751080	0.326923
61	-0.25	0.5	-0.5	-0.422420	-0.409968	-0.344644	-0.550725	0.326923
62	-0.25	0.5	0.5	-0.487267	-0.456093	-0.344110	0.128520	0.326923
63	-1	-1	-1	-0.607281	-0.698481	-0.568312	-0.287767	0.519238
64	-1	-1	0	0.060297	-0.188252	0.033343	0.669479	0.519238
65	-1	-1	1	0.055221	-0.151222	0.313575	-0.057580	0.519238
66	-1	0	-1	-0.177033	-0.658813	-0.569469	-0.705940	0.519238
67	-1	0	0	-0.242948	-0.388054	-0.162832	0.384182	0.519238
68	-1	0	1	-0.063407	-0.250549	0.044357	-0.092229	0.519238
69	-1	1	-1	-0.693197	-0.699754	-0.538398	-0.814768	0.519238
70	-1	1	0	-0.495307	-0.565259	-0.555758	-0.804660	0.519238
71	-1	1	1	-0.195668	-0.461897	-0.075541	-0.598551	0.519238
72	0	-1	-1	-0.490788	-0.580376	-0.640652	-0.200875	0.519238
73	0	-1	0	-0.556447	-0.658751	-0.452699	-0.242782	0.519238
74	0	-1	1	-0.634773	-0.718036	-0.535846	-0.431015	0.519238
75	0	0	-1	-0.632593	-0.885557	-0.728781	-0.168879	0.519238
76	0	0	0	-0.734389	-0.826923	-0.661079	0.044502	0.519238
77	0	0	1	-0.823009	-0.928050	-0.736483	-0.746588	0.519238
78	0	1	-1	-0.638674	-0.695874	-0.534463	0.070720	0.519238
79	0	1	0	-0.411956	-0.535989	-0.355534	-0.360497	0.519238
80	0	1	1	-0.576638	-0.684079	-0.525233	-0.430334	0.519238
81	1	-1	-1	-0.441771	-0.457769	-0.291850	0.384103	0.519238
82	1	-1	0	-0.819462	-0.824285	-0.725745	-0.675586	0.519238
83	1	-1	1	-0.926229	-0.869696	-0.790533	-0.912447	0.519238
84	1	0	-1	-0.697153	-0.636154	-0.631401	-0.635854	0.519238
85	1	0	0	-0.693700	-0.730607	-0.656822	-0.545736	0.519238
86	1	0	1	-0.589833	-0.523852	-0.563227	-0.509171	0.519238
87	1	1	-1	-0.714262	-0.738957	-0.695271	-0.826597	0.519238
88	1	1	0	-0.734257	-0.752925	-0.731077	-0.722074	0.519238
89	1	1	1	-0.932482	-0.829034	-0.830504	-0.396988	0.519238
90	-0.75	-0.5	-0.5	-0.176471	-0.227362	-0.154963	0.077695	0.711538
91	-0.75	-0.5	0.5	-0.171094	-0.225624	-0.191433	0.596329	0.711538
92	-0.75	0.5	-0.5	0.787902	0.554339	0.690509	1.000000	0.711538
93	-0.75	0.5	0.5	0.079369	0.158491	-0.056957	0.668269	0.711538

Exp #	S	F	D	X	Y	Z	W	Tool Wear
94	-0.25	-0.5	-0.5	0.110961	1.000000	-0.000082	0.093925	0.711538
95	-0.25	-0.5	0.5	-0.455176	-0.452430	-0.329596	-0.349559	0.711538
96	-0.25	0.5	-0.5	-0.211044	-0.235153	-0.193558	0.126114	0.711538
97	-0.25	0.5	0.5	-0.279320	-0.234067	-0.193135	0.001375	0.711538
98	-1	-1	-1	-0.620874	-0.491106	-0.549228	-0.123364	0.903841
99	-1	-1	0	-0.070090	-0.069526	0.090473	0.218544	0.903841
100	-1	-1	1	0.266439	-0.000400	0.146719	0.081181	0.903841
101	-1	0	-1	-0.292084	-0.601979	-0.712692	-0.449457	0.903841
102	-1	0	0	-0.235765	-0.560541	-0.189009	0.748624	0.903841
103	-1	0	1	-0.065786	-0.207993	0.070829	-0.103510	0.903841
104	-1	1	-1	-0.599985	-0.968681	-0.601495	-0.238798	0.903841
105	-1	1	0	-0.506799	-0.739205	-0.521286	-0.914498	0.903841
106	-1	1	1	-0.859639	-0.679826	-0.740061	-0.516586	0.903841
107	0	-1	-1	-0.413489	-0.410061	-0.356690	-0.056960	0.903841
108	0	-1	0	-0.502115	-0.692677	-0.488957	-0.181523	0.903841
109	0	-1	1	-0.551263	-0.488653	-0.505168	-0.223805	0.903841
110	0	0	-1	-0.390136	-0.510630	-0.535893	-0.232052	0.903841
111	0	0	0	-0.790441	-0.716608	-0.680275	0.303120	0.903841
112	0	0	1	-0.709192	-0.709997	-0.712628	-0.760584	0.903841
113	0	1	-1	-0.651830	-0.603655	-0.599256	-0.158124	0.903841
114	0	1	0	-0.557003	-0.455224	-0.429399	-0.399814	0.903841
115	0	1	1	-0.639356	-0.587701	-0.557910	-0.595445	0.903841
116	1	-1	-1	-0.327492	-0.305706	-0.282347	0.299225	0.903841
117	1	-1	0	-0.861985	-0.754135	-0.756931	-0.600222	0.903841
118	1	-1	1	-0.908801	-0.787348	-0.787358	-0.790079	0.903841
119	1	0	-1	-0.557548	-0.444546	-0.438946	-0.418406	0.903841
120	1	0	0	-0.903149	-0.807834	-0.807679	-0.746827	0.903841
121	1	0	1	-0.614708	-0.552999	-0.600202	-0.391779	0.903841
122	1	1	-1	-0.906659	-0.822795	-0.827572	-0.639270	0.903841
123	1	1	0	-0.935324	-0.806903	-0.829016	-0.879264	0.903841
124	1	1	1	-0.950509	-0.759878	-0.821879	-0.586825	0.903841
125	-1	-1	-1	-0.654163	-0.860912	-0.515761	0.373708	1.000000
126	-1	-1	0	-0.029930	-0.080358	0.045497	0.506053	1.000000
127	-1	-1	1	0.271276	-0.102366	0.159001	-0.114280	1.000000
128	-1	0	-1	-0.446716	-0.589843	-0.509363	-0.889340	1.000000
129	-1	0	0	-0.074729	-0.385354	-0.067621	0.566379	1.000000
130	-1	0	1	0.272281	-0.032806	0.204531	0.257361	1.000000
131	-1	1	-1	-0.690513	-0.747338	-0.610259	-0.734292	1.000000
132	-1	1	0	-0.480658	-0.535058	-0.544939	-0.786836	1.000000
133	-1	1	1	-0.257182	-0.275939	1.000000	-0.469520	1.000000
134	0	-1	-1	-0.419201	-0.457583	-0.460476	-0.094977	1.000000
135	0	-1	0	-0.449163	-0.659278	-0.450259	0.006385	1.000000
136	0	-1	1	-0.447182	-0.730856	-0.545950	0.297559	1.000000
137	0	0	-1	-0.286650	-0.593847	-0.369741	-0.019235	1.000000
138	0	0	0	-0.830073	-0.869013	-0.727365	0.114890	1.000000
139	0	0	1	-0.750794	-0.748952	-0.658586	-0.795004	1.000000
140	0	1	-1	-0.716586	-0.613215	-0.604930	-0.431778	1.000000

Exp #	S	F	D	X	Y	Z	W	Tool Wear
141	0	1	0	-0.484536	-0.338546	-0.410301	0.416577	1.000000
142	0	1	1	-0.692467	-0.634943	-0.598904	-0.607839	1.000000
143	1	-1	-1	-0.396063	-0.285779	-0.275766	0.714984	1.000000
144	1	-1	0	-0.920833	-0.781823	-0.784348	-0.606869	1.000000
145	1	-1	1	-0.936378	-0.712542	-0.746450	0.196874	1.000000
146	1	0	-1	-0.796922	-0.654157	-0.661916	-0.288179	1.000000
147	1	0	0	-0.946779	-0.815128	-0.825127	-0.428120	1.000000
148	1	0	1	-0.663103	-0.491323	-0.593545	-0.540086	1.000000
149	1	1	-1	-0.966496	-0.768351	-0.831639	-0.557012	1.000000
150	1	1	0	-0.989006	-0.824937	-0.866866	-0.295752	1.000000
151	1	1	1	-1.000000	-0.828289	-0.882045	-0.647779	1.000000

APPENDIX I. TEST RESULT OF ANN MODEL

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
1	500	0.01	0.01	0.103408	-1.430820	-0.015699	0.270185	0.001071	SHARP	SHARP
2	500	0.01	0.02	0.235751	-1.285750	0.237133	0.616138	0.001071	SHARP	SHARP
3	500	0.01	0.03	0.076789	-1.411080	0.039403	0.251949	0.001071	SHARP	SHARP
4	500	0.02	0.01	0.170515	-1.366040	0.141927	0.174760	0.001071	SHARP	SHARP
5	500	0.02	0.02	0.200056	-1.288690	0.187773	0.589756	0.001071	SHARP	SHARP
6	500	0.02	0.03	0.247586	-1.311110	0.268844	0.321340	0.001071	SHARP	SHARP
7	500	0.03	0.01	0.127092	-1.410120	0.109214	0.312770	0.001071	SHARP	SHARP
8	500	0.03	0.02	0.133569	-1.354480	0.105598	0.272689	0.001071	SHARP	SHARP
9	500	0.03	0.03	0.210960	-1.279870	0.237261	0.256727	0.001071	SHARP	SHARP
10	1000	0.01	0.01	0.167376	-1.321790	0.147443	0.452802	0.001071	SHARP	SHARP
11	1000	0.01	0.02	0.049992	-1.448490	-0.017632	0.241961	0.001071	SHARP	SHARP
12	1000	0.01	0.03	0.108134	-1.389200	0.062495	0.310213	0.001071	SHARP	SHARP
13	1000	0.02	0.01	0.113586	-1.421800	0.056752	0.281919	0.001071	SHARP	SHARP
14	1000	0.02	0.02	0.071487	-1.440050	-0.004799	0.322865	0.001071	SHARP	SHARP
15	1000	0.02	0.03	0.068075	-1.430540	0.023443	0.226214	0.001071	SHARP	SHARP
16	1000	0.03	0.01	0.099139	-1.375040	0.053323	0.299417	0.001071	SHARP	SHARP
17	1000	0.03	0.02	0.122677	-1.325910	0.061883	0.279658	0.001071	SHARP	SHARP
18	1000	0.03	0.03	0.120279	-1.349690	0.096196	0.371440	0.001071	SHARP	SHARP
19	1500	0.01	0.01	0.148157	-1.293570	0.092410	0.607875	0.001071	SHARP	SHARP
20	1500	0.01	0.02	0.062347	-1.434630	-0.006021	0.335853	0.001071	SHARP	SHARP
21	1500	0.01	0.03	0.058911	-1.439940	-0.013007	0.234790	0.001071	SHARP	SHARP
22	1500	0.02	0.01	0.082214	-1.399790	0.008395	0.195683	0.001071	SHARP	SHARP
23	1500	0.02	0.02	0.061900	-1.444340	-0.019831	0.206459	0.001071	SHARP	SHARP
24	1500	0.02	0.03	0.098103	-1.363160	0.018559	0.274516	0.001071	SHARP	SHARP
25	1500	0.03	0.01	0.055068	-1.441880	-0.010812	0.222817	0.001071	SHARP	SHARP
26	1500	0.03	0.02	0.048699	-1.441190	-0.018885	0.425353	0.001071	SHARP	SHARP
27	1500	0.03	0.03	0.045472	-1.446870	-0.028010	0.336833	0.001071	SHARP	SHARP
28	500	0.01	0.01	0.157653	-1.360240	0.109958	0.388926	0.003571	SHARP	SHARP
29	500	0.01	0.02	0.312557	-1.014820	0.225042	0.776312	0.003571	SHARP	SHARP
30	500	0.01	0.03	0.402947	-1.085880	0.389177	0.491272	0.003571	SHARP	SHARP
31	500	0.02	0.01	0.078818	-1.402400	0.040810	0.269807	0.003571	SHARP	SHARP
32	500	0.02	0.02	0.316836	-1.093630	0.274146	0.744495	0.003571	SHARP	SHARP
33	500	0.02	0.03	0.380662	-0.949184	0.365038	0.621417	0.003571	SHARP	SHARP
34	500	0.03	0.01	0.138932	-1.312830	0.103167	0.491345	0.003571	SHARP	SHARP
35	500	0.03	0.02	0.164012	-1.308930	0.083374	0.294990	0.003571	SHARP	SHARP
36	500	0.03	0.03	0.283327	-1.138160	0.185009	0.511798	0.003571	SHARP	SHARP
37	1000	0.01	0.01	0.055086	-1.434720	0.027233	0.286314	0.003571	SHARP	SHARP
38	1000	0.01	0.02	0.209076	-1.163180	0.220595	0.604607	0.003571	SHARP	SHARP
39	1000	0.01	0.03	0.144785	-1.301620	0.165560	0.441347	0.003571	SHARP	SHARP
40	1000	0.02	0.01	0.165041	-1.258760	0.146440	0.632799	0.003571	SHARP	SHARP
41	1000	0.02	0.02	0.094754	-1.385110	0.077946	0.453860	0.003571	SHARP	SHARP
42	1000	0.02	0.03	0.067176	-1.404550	0.043388	0.242044	0.003571	SHARP	SHARP
43	1000	0.03	0.01	0.126813	-1.334230	0.111111	0.297358	0.003571	SHARP	SHARP
44	1000	0.03	0.02	0.178965	-1.274100	0.153053	0.550548	0.003571	SHARP	SHARP

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
45	1000	0.03	0.03	0.113742	-1.338350	0.095795	0.293120	0.003571	SHARP	SHARP
46	1500	0.01	0.01	0.217801	-1.177760	0.234067	0.646128	0.003571	SHARP	SHARP
47	1500	0.01	0.02	0.075499	-1.420060	0.047443	0.307347	0.003571	SHARP	SHARP
48	1500	0.01	0.03	0.065546	-1.443970	0.028053	0.130060	0.003571	SHARP	SHARP
49	1500	0.02	0.01	0.084877	-1.399261	0.022930	0.216916	0.003571	SHARP	SHARP
50	1500	0.02	0.02	0.067586	-1.426220	0.029051	0.207792	0.003571	SHARP	SHARP
51	1500	0.02	0.03	0.104926	-1.363340	0.071226	0.355754	0.003571	SHARP	SHARP
52	1500	0.03	0.01	0.066417	-1.429250	0.035396	0.212281	0.003571	SHARP	SHARP
53	1500	0.03	0.02	0.057071	-1.432870	0.020671	0.497980	0.003571	SHARP	SHARP
54	1500	0.03	0.03	0.052607	-1.447260	0.016440	0.245869	0.003571	SHARP	SHARP
55	625	0.015	0.015	0.126559	-1.347390	0.131868	0.367391	0.007143	**SHARP**	**WORN**
56	625	0.015	0.025	0.103143	-1.388570	0.074497	0.323327	0.007143	**SHARP**	**WORN**
57	625	0.025	0.015	0.258450	1.778820	1.619050	0.508638	0.007143	SHARP	SHARP
58	625	0.025	0.025	0.149315	-1.279530	0.157199	0.426325	0.007143	**SHARP**	**WORN**
59	875	0.015	0.015	0.234535	-1.295910	0.181497	0.334757	0.007143	**SHARP**	**WORN**
60	875	0.015	0.025	0.100786	-1.387800	0.017358	0.230901	0.007143	SHARP	SHARP
61	875	0.025	0.015	0.140870	-1.324880	0.136395	0.312068	0.007143	SHARP	SHARP
62	875	0.025	0.025	0.129449	-1.339740	0.136529	0.587240	0.007143	**SHARP**	**WORN**
63	500	0.01	0.01	0.108312	-1.417830	0.080285	0.418596	0.010714	WORN	WORN
64	500	0.01	0.02	0.225887	-1.253450	0.231218	0.806390	0.010714	WORN	WORN
65	500	0.01	0.03	0.224993	-1.241520	0.301518	0.511848	0.010714	WORN	WORN
66	500	0.02	0.01	0.184088	-1.405050	0.079995	0.249188	0.010714	WORN	WORN
67	500	0.02	0.02	0.172479	-1.317820	0.182005	0.690812	0.010714	WORN	WORN
68	500	0.02	0.03	0.204100	-1.273520	0.233981	0.497811	0.010714	WORN	WORN
69	500	0.03	0.01	0.093180	-1.418240	0.087789	0.205100	0.010714	WORN	WORN
70	500	0.03	0.02	0.128033	-1.374910	0.083434	0.209195	0.010714	WORN	WORN
71	500	0.03	0.03	0.180806	-1.341610	0.203903	0.292693	0.010714	WORN	WORN
72	1000	0.01	0.01	0.128829	-1.379780	0.062138	0.453797	0.010714	WORN	WORN
73	1000	0.01	0.02	0.117265	-1.405030	0.109288	0.436820	0.010714	WORN	WORN
74	1000	0.01	0.03	0.103470	-1.424130	0.088429	0.360564	0.010714	WORN	WORN
75	1000	0.02	0.01	0.103854	-1.478100	0.040029	0.466759	0.010714	WORN	WORN
76	1000	0.02	0.02	0.085926	-1.459210	0.057013	0.553203	0.010714	WORN	WORN
77	1000	0.02	0.03	0.070318	-1.491790	0.038097	0.232721	0.010714	WORN	WORN
78	1000	0.03	0.01	0.102783	-1.416990	0.088776	0.563824	0.010714	WORN	WORN
79	1000	0.03	0.02	0.142713	-1.365480	0.133663	0.389132	0.010714	WORN	WORN
80	1000	0.03	0.03	0.113709	-1.413190	0.091092	0.360840	0.010714	WORN	WORN
81	1500	0.01	0.01	0.137462	-1.340280	0.149639	0.690780	0.010714	WORN	WORN
82	1500	0.01	0.02	0.070942	-1.458360	0.040791	0.261485	0.010714	WORN	WORN
83	1500	0.01	0.03	0.052138	-1.472990	0.024538	0.165529	0.010714	WORN	WORN
84	1500	0.02	0.01	0.092484	-1.397750	0.064458	0.277581	0.010714	WORN	WORN
85	1500	0.02	0.02	0.093092	-1.428180	0.058081	0.314089	0.010714	WORN	WORN
86	1500	0.02	0.03	0.111385	-1.361570	0.081560	0.328902	0.010714	WORN	WORN
87	1500	0.03	0.01	0.089470	-1.430870	0.048435	0.200308	0.010714	WORN	WORN
88	1500	0.03	0.02	0.085949	-1.435370	0.039453	0.242652	0.010714	WORN	WORN
89	1500	0.03	0.03	0.051037	-1.459890	0.014510	0.374349	0.010714	WORN	WORN
90	625	0.015	0.015	0.184187	-1.266050	0.183979	0.566650	0.014286	WORN	WORN
91	625	0.015	0.025	0.185134	-1.265490	0.174830	0.776756	0.014286	WORN	WORN

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
92	625	0.025	0.015	0.354034	-1.014210	0.396077	0.940289	0.014286	WORN	WORN
93	625	0.025	0.025	0.229246	-1.141740	0.208565	0.805900	0.014286	WORN	WORN
94	875	0.015	0.015	0.234810	-0.870632	0.222833	0.573225	0.014286	WORN	WORN
95	875	0.015	0.025	0.135101	-1.338560	0.140170	0.393563	0.014286	WORN	WORN
96	875	0.025	0.015	0.178098	-1.268560	0.174297	0.586265	0.014286	WORN	WORN
97	875	0.025	0.025	0.166073	-1.268210	0.174403	1.038900	0.014286	WORN	WORN
98	500	0.01	0.01	0.105918	-1.351020	0.085072	0.485198	0.017857	WORN	WORN
99	500	0.01	0.02	0.202923	-1.215200	0.245550	0.623710	0.017857	WORN	WORN
100	500	0.01	0.03	0.262193	-1.192930	0.259660	0.568062	0.017857	WORN	WORN
101	500	0.02	0.01	0.163825	-1.386740	0.044065	0.353093	0.017857	WORN	WORN
102	500	0.02	0.02	0.173744	-1.373390	0.175438	0.838453	0.017857	WORN	WORN
103	500	0.02	0.03	0.203681	-1.259810	0.240622	0.493241	0.017857	WORN	WORN
104	500	0.03	0.01	0.109597	-1.504880	0.071961	0.438434	0.017857	WORN	WORN
105	500	0.03	0.02	0.126009	-1.430950	0.092082	0.164698	0.017857	WORN	WORN
106	500	0.03	0.03	0.063866	-1.411820	0.037199	0.325898	0.017857	WORN	WORN
107	1000	0.01	0.01	0.142443	-1.324910	0.133373	0.512099	0.017857	WORN	WORN
108	1000	0.01	0.02	0.126834	-1.415960	0.100192	0.461637	0.017857	WORN	WORN
109	1000	0.01	0.03	0.118178	-1.350230	0.096125	0.444508	0.017857	WORN	WORN
110	1000	0.02	0.01	0.146556	-1.357310	0.088418	0.441167	0.017857	WORN	WORN
111	1000	0.02	0.02	0.076054	-1.423670	0.052198	0.657973	0.017857	WORN	WORN
112	1000	0.02	0.03	0.090363	-1.421540	0.044081	0.227051	0.017857	WORN	WORN
113	1000	0.03	0.01	0.100466	-1.387280	0.072522	0.471116	0.017857	WORN	WORN
114	1000	0.03	0.02	0.117167	-1.339460	0.115133	0.373204	0.017857	WORN	WORN
115	1000	0.03	0.03	0.102663	-1.382140	0.082894	0.293951	0.017857	WORN	WORN
116	1500	0.01	0.01	0.157589	-1.291290	0.152023	0.656395	0.017857	WORN	WORN
117	1500	0.01	0.02	0.063453	-1.435760	0.032967	0.292016	0.017857	WORN	WORN
118	1500	0.01	0.03	0.055208	-1.446460	0.025334	0.215102	0.017857	WORN	WORN
119	1500	0.02	0.01	0.117071	-1.336020	0.112738	0.365672	0.017857	WORN	WORN
120	1500	0.02	0.02	0.056203	-1.453060	0.020237	0.232624	0.017857	WORN	WORN
121	1500	0.02	0.03	0.107004	-1.370960	0.072285	0.376459	0.017857	WORN	WORN
122	1500	0.03	0.01	0.055585	-1.457880	0.015246	0.276197	0.017857	WORN	WORN
123	1500	0.03	0.02	0.050537	-1.452760	0.014884	0.178972	0.017857	WORN	WORN
124	1500	0.03	0.03	0.047862	-1.437610	0.016674	0.297443	0.017857	WORN	WORN
125	500	0.01	0.01	0.100055	-1.470160	0.093468	0.686569	0.019643	WORN	WORN
126	500	0.01	0.02	0.209996	-1.218690	0.234267	0.740184	0.019643	WORN	WORN
127	500	0.01	0.03	0.263045	-1.225780	0.262741	0.488878	0.019643	WORN	WORN
128	500	0.02	0.01	0.136591	-1.382830	0.095073	0.174890	0.019643	WORN	WORN
129	500	0.02	0.02	0.202106	-1.316950	0.205890	0.764623	0.019643	WORN	WORN
130	500	0.02	0.03	0.263222	-1.203370	0.274163	0.639435	0.019643	WORN	WORN
131	500	0.03	0.01	0.093653	-1.433570	0.069762	0.237702	0.019643	WORN	WORN
132	500	0.03	0.02	0.130613	-1.365180	0.086148	0.216416	0.019643	WORN	WORN
133	500	0.03	0.03	0.169972	-1.281700	0.473717	0.344965	0.019643	WORN	WORN
134	1000	0.01	0.01	0.141437	-1.340220	0.107337	0.496698	0.019643	WORN	WORN
135	1000	0.01	0.02	0.136160	-1.405200	0.109900	0.537761	0.019643	WORN	WORN
136	1000	0.01	0.03	0.136509	-1.428260	0.085895	0.655720	0.019643	WORN	WORN
137	1000	0.02	0.01	0.164782	-1.384120	0.130099	0.527382	0.019643	WORN	WORN
138	1000	0.02	0.02	0.069074	-1.472770	0.040384	0.581718	0.019643	WORN	WORN

Exp #	S	F	D	X	Y	Z	W	Tool Wear	Condition	Result
139	1000	0.02	0.03	0.083036	-1.434090	0.057638	0.213107	0.019643	WORN	WORN
140	1000	0.03	0.01	0.089061	-1.390360	0.071099	0.360255	0.019643	WORN	WORN
141	1000	0.03	0.02	0.129930	-1.301870	0.119924	0.703936	0.019643	WORN	WORN
142	1000	0.03	0.03	0.093309	-1.397360	0.072610	0.288930	0.019643	WORN	WORN
143	1500	0.01	0.01	0.145512	-1.284870	0.153674	0.824825	0.019643	WORN	WORN
144	1500	0.01	0.02	0.053089	-1.444680	0.026089	0.289323	0.019643	WORN	WORN
145	1500	0.01	0.03	0.050351	-1.422360	0.035597	0.614931	0.019643	WORN	WORN
146	1500	0.02	0.01	0.074912	-1.403550	0.056803	0.418429	0.019643	WORN	WORN
147	1500	0.02	0.02	0.048519	-1.455410	0.015859	0.361737	0.019643	WORN	WORN
148	1500	0.02	0.03	0.098481	-1.351090	0.073955	0.316378	0.019643	WORN	WORN
149	1500	0.03	0.01	0.045046	-1.440340	0.014226	0.309521	0.019643	WORN	WORN
150	1500	0.03	0.02	0.041082	-1.458570	0.005388	0.415361	0.019643	WORN	WORN
151	1500	0.03	0.03	0.039146	-1.459650	0.001581	0.272750	0.019643	WORN	WORN

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